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BAKER BOTTS LLP TRANSMITTAL LETTER TO THE UNITED STATES DESIGNATED/ELECTED OFFICE (DO/EO/US) CONCERNING A FILING UNDER 35.U.S.C. 371	EXPRESS MAIL LABEL No. EL866934376US	DATE 10/25/01
	ATTORNEY'S DOCKET NO. A34703-PCT-USA	
	U.S. APPLICATION NO. t/b/a 10/019362	
INTERNATIONAL APPLICATION NO. PCT/CH01/00136	INTERNATIONAL FILING DATE March 6, 2000	PRIORITY DATE CLAIMED March 15, 2000

TITLE OF INVENTION METHOD FOR PROCESSING THE SIGNALS OF A DANGER DETECTOR AND DANGER DETECTOR HAVING MEANS FOR PERFORMING THE METHOD

APPLICANT(S) FOR DO/EO/US Marc Pierre Thuillard

Applicant herewith submits to the United States Designated /Elected Office (DO/EO/US) the following items and other information:

1. [✓] This is a FIRST submission of items concerning a filing under 35 U.S.C. 371.
2. [ ] This is a SECOND or SUBSEQUENT submission of items concerning a filing under 35 U.S.C. 371.
3. [ ] This express request to begin national examination procedures (35 U.S.C. 371(f)) at any time rather than delay examination until the expiration of the applicable time limit set in 35 U.S.C. 371(b) and PCT Articles 22 and 39(I).
4. [✓] A proper Demand for International Preliminary Examination was made by the 19th month from the earliest claimed priority date.
5. [✓] A copy of the International Application as filed (35 U.S.C. 371(c)(2))
   a. [ ] is transmitted herewith (required only if not transmitted by the International Bureau).
   b. [✓] has been transmitted by the International Bureau.
   c. [ ] is not required, as the application was filed in the United States Receiving Office (RO/US).
6. [✓] A translation of the International Application into English (35 U.S.C. 371(c)(2)).
7. [✓] A copy of the International Search Report (PCT/ISA/210)
   a. [ ] are transmitted herewith (required only if not transmitted by the International Bureau).
   b. [ ] have been transmitted by the International Bureau
   c. [ ] have not been made; however, the time limit for making such amendments has NOT expired.
   d. [ ] have not been made and will not be made.
8. [✓] A translation of the amendments to the claims under PCT Article 19 (35 U.S.C. 371(c)(3)).
9. [ ] An oath or declaration of the inventor(s) (35 U.S.C. 371(c)(4)).
10. [ ] A translation of the annexes to the International Preliminary Examination Report under PCT Article 36 (35 U.S.C. 371(c)(5)).

Items 11. to 16. below concern other document(s) or information included:

11. [ ] A copy of the International Preliminary Examination Report (PCT/IPEA/409)
12. [ ] An assignment document for recording. A separate cover sheet in compliance with 37 CFR 3.28 and 3.31 is included.
13. [✓] A FIRST preliminary amendment.
    [ ] A SECOND or SUBSEQUENT preliminary amendment.
14. [✓] A substitute specification.
15. [ ] A change of power of attorney and/or address letter.
16. [ ] Other items or information:
    a. [ ] a copy of the International Search Report (PCT/ISA/210)
    b. [ ] a copy of the International Preliminary Examination Report (PCT/IPEA/409)

Comparison document; English and German versions of application; cover page of PCT international application; formal drawings (Figs. 1-4); postcard; check in the amount of $710.00.

10/019362

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INTERNATIONAL APPLICATION NO.	INTERNATIONAL FILING DATE	PRIORITY DATE CLAIMED
PCT/CH01/00136	March 6, 2000	March 15, 2000

	CALCULATIONS	PTO USE ONLY
17. [ ] The following fees are submitted: **Basic National Fee (37 CFR 1.492(a)(1)-(5):** Neither international preliminary examination fee (37 CFR 1.482) Nor international search fee (37 CFR 1.445(a)(2)) paid to USPTO and International Search Report not prepared by the EPO or JPO (1.492(a)(3)) $1,040 International preliminary examination fee (37 CFR 1.482) not paid to USPTO but International Search Report prepared by the EPO or JPO (1.492(a)(5) $890.00 International preliminary examination fee (37 CFR 1.482) not paid to USPTO but international search fee (37 CFR 1.445(a)(2)) paid to USPTO(1.492(a)(2)) $740.00 International preliminary examination fee paid to USPTO (37 CFR 1.482) but all claims did not satisfy provisions of PCT Article 33(1)-(4) (1.492(a)(1)) $710.00 International preliminary examination fee paid to USPTO (37 CFR 1.482) and all claims satisfied provisions of PCT Article 33(1)-(4) $ 100.00		
ENTER APPROPRIATE BASIC FEE AMOUNT =	$ 740	
Surcharge of $130.00 for furnishing the oath or declaration later than [ ] 20 [ ] 30 months from the earliest claimed priority date (37 C.F.R. 1.492)(e)).	$	

Claims	Number Filed	Number Extra	Rate	$	
Total Claims	12 -20=	0	X $ 18.00	$ 0	
Independent Claims	1 -3=	0	X $ 84.00	$ 0	
Multiple dependent claim(s) (if applicable)			+ $280.00	$	
TOTAL OF ABOVE CALCULATIONS =				$ 740	
Reduction by ½ for filing by small entity, if applicable.				$	
SUBTOTAL =				$ 740	
Processing fee of $130.00 for furnishing the English translation later than [ ] 20 [ ] 30 months from the earliest claimed priority date (37 CFR 1.492(f)). +				$	
TOTAL NATIONAL FEE =				$ 740	
Fee for recording the enclosed assignment (37 CFR 1.21(h)). The assignment must be accompanied by an appropriate cover sheet (37 CFR 3.28, 3.31). $40.00 per property +				$	
TOTAL FEES ENCLOSED =				$ 740	
				Amt. refunded	$
				charged	$

a. [✓] A check in the amount of $740.00 to cover the above fees is enclosed.

b. [ ] Please charge our Deposit Account No. 02-4377 in amount of $________ to cover the above fees. A copy of this sheet is enclosed.

c. [✓] The Commissioner is hereby authorized to charge any additional fees which may be required, or credit any overpayment to Deposit Account No. 02-4377. A copy of this sheet is enclosed.

NOTE: Where an appropriate time limit under 37 CFR 1.494 or 1.495 has not been met, a petition to revive (37 CFR 1.137(a) or (b)) must be filed and granted to restore the application to pending status.

SEND ALL CORRESPONDENCE TO:
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10/25/01
Date

10/019362

A34703-PCT-USA (070256.0214)

PATENT

531 Rec'd PCT/ 25 OCT 2001

IN THE UNITED STATES PATENT AND TRADEMARK OFFICE

Inventor(s)	:	THUILLARD
Serial No.	:	To Be Assigned
Filed	:	Herewith
For	:	**METHOD FOR PROCESSING THE SIGNALS OF A DANGER DETECTOR AND DANGER DETECTOR HAVING MEANS FOR PERFORMING THE METHOD**
Examiner	:	To Be Assigned
Group Art Unit	:	To Be Assigned

Assistant Commissioner for Patents
Washington, DC 20231

PRELIMINARY AMENDMENT

Sir:

Kindly amend the above-identified application before examination as follows:

IN THE SPECIFICATION:

Please substitute the originally-filed specification with the Substitute Specification which is enclosed herewith. A comparison document showing the differences between the translation of the originally-filed specification and the enclosed Substitute Specification is also enclosed herewith.

IN THE ABSTRACT:

Cancel the Abstract as originally filed and substitute the following:

--The signals of a danger detector that has at least one sensor (2, 3, 4) for monitoring danger parameters and an electronic evaluation system (1) assigned to the at least one sensor (2, 3, 4) are compared with specified parameters. In addition, the signals are analyzed with regard to whether they occur increasingly frequently or regularly, and signals that occur increasingly frequently or regularly are classified as interference signals. The classification of signals as interference signals triggers an appropriate adjustment of the parameters. If interference signals occur, the validity of the result of the analysis of the signals of the at least one sensor (2, 3, 4) is checked prior to the adjustment of the parameters, and the parameters are adjusted as a function of the result of said validity test.

A danger detector having means for carrying out said method contains at least one sensor (2, 3, 4) for a danger parameter and an electronic evaluation system (1), comprising a microprocessor (6), for evaluating and analyzing the signals of the at least one sensor (2, 3, 4). The microprocessor (6) comprises a software program having a learning algorithm, based on multiple resolution, for analyzing the signals of the at least one sensor (2, 3,'4).—

A "Version With Marked Changes Made" is submitted herewith.

IN THE CLAIMS:

Please cancel original claims 1-11 in the underlying PCT application, without prejudice.

Please add new claims 12-23, as follows:

--12. A method for processing signals of a detector comprising at least one sensor for monitoring danger parameters and an electronic evaluation system assigned to the at least one sensor wherein signals from the at least one sensor are compared with specified parameters, and the signals are analyzed on the basis of their occurrence and depending on their occurrence pattern are classified as interference signals.

13. A method according to Claim 1, wherein the classification of signals as interference signals triggers an appropriate adjustment of the parameters.

14. A method according to Claim 2, wherein the analysis of the signals to determine its validity is tested prior to the adjustment of the parameters and the parameters are adjusted as a function of the validity test.

15. method according to Claim 3, wherein the validity is tested by methods based on multiple resolution.

16. Method according to Claim 4, wherein wavelets, selected from the group consisting of biorthogonal and second generation wavelets and lifting schemes are used for the validity test.

17. A method according to Claim 5, wherein coefficients of the wavelets selected from the group consisting of approximation coefficients, and approximation coefficients

and detailed coefficients have expected values which are determined and compared at different resolutions.

18. A method according to Claim 6, wherein the coefficients are determined in an estimator.

19. A method according to Claim 6, wherein the coefficients are determined by means of a neuronal network.

20. A detector for carrying out the method according to Claim 1, comprising at least one sensor for sensing a danger parameter and an electronic evaluation system comprising a microprocessor for evaluating and analyzing signals emitted from at least one sensor wherein the microprocessor comprises a software program having a learning algorithm, based on multiple resolution, for analyzing the signals of the at least one sensor.

21. A detector according to Claim 9, wherein the sensor signals are analyzed by the learning algorithm for their occurrence and a validity test is carried out on the analysis by a learning algorithm which uses wavelets selected from the group consisting of biorthogonal and second generation - - - - and lifting schemes.

22. A detector according to Claim 9, wherein in that the learning algorithm uses neuro-fuzzy methods.

23. A detector according to Claim 10, wherein the learning algorithm comprises two equations

$$f_m(x) = \sum \widehat{c}_{m,n} \cdot \varphi_{m,n}(x) \text{ (}\Sigma\text{over all n's) and}$$
$$\widehat{c}_{m,n}(k) = \sum \widetilde{\varphi}_{m,n}(x_i) \cdot y_i / \sum \widetilde{\varphi}_{m,n}(x_i) \text{ (}\Sigma\text{over all i's} = 1 \text{ to } k\text{),}$$

in which $\varphi_{m,n}$ denotes scaling functions, $\hat{c}_{m,n}$ denotes approximation coefficients and y_k denotes the k[th] input point of the neuronal network and $\widetilde{\varphi}_{m,n}$ is the dual function of $\varphi_{m,n}$.--

REMARKS

This Preliminary Amendment cancels, without prejudice, originally-filed claims 1-11 in underlying PCT Application No. PCT/CH01/00136. New claims 12-23 have been added merely to conform the claims to U.S. Patent and Trademark Office practice and standards, and do not add new matter to the application. Furthermore, the addition of these new claims in no way addresses any issues of patentability, and the new claims are provided to place the application in condition for allowance.

The amendment to the abstract and the substitute specification are provided to conform the specification and abstract of the above-identified application to the U.S. Patent and Trademark Office practice, and do not introduce new matter into the application.

The amendments to the "Abstract" and "Claims" are reflected in the attached "Version With Marked Changes Made."

Applicant asserts that the present invention is new, non-obvious, and useful. Favorable consideration and allowance of the claims are respectfully requested.

Respectfully submitted,

Dated: October 25, 2001

By: ______________________

Bradley B. Geist
Reg. No. 27,551

BAKER BOTTS L.L.P.
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Version With Marked Changes Made

CLAIMS:

~~1.~~12. ~~Method~~A method for processing ~~the~~ signals of a detector ~~unit that has~~comprising at least one sensor ~~(2, 3, 4)~~ for monitoring danger parameters and an electronic evaluation system ~~(1)~~ ~~that is~~ assigned to the at least one sensor ~~(2, 3, 4) and in which the~~wherein signals ~~of~~from the at least one sensor ~~(2, 3, 4)~~ are compared with specified parameters, ~~characterized in that~~and the signals ~~of the at least one sensor (2, 3, 4)~~ are analyzed on the basis of ~~whether they occur increasingly frequently or regularly~~their occurrence and ~~in that signals occurring increasingly frequently or regularly~~depending on their occurrence pattern are classified as interference signals.

~~2.~~13. ~~Method~~A method according to Claim 1, ~~characterized in that~~wherein the classification of signals as interference signals triggers an appropriate adjustment of the parameters.

~~3.~~14. ~~Method~~A method according to Claim 2, ~~characterized in that, if interference signals occur, the validity of the result of~~wherein the analysis of the signals ~~of the at least one sensor (2, 3, 4)~~to determine its validity is ~~checked~~tested prior to the adjustment of the parameters and ~~in that~~ the parameters are adjusted as a function of the ~~result of this~~ validity test.

~~4.~~15. ~~Method~~A method according to Claim 3, ~~characterized in that~~wherein the validity is tested by methods based on multiple resolution.

~~5.~~16. ~~Method~~A method according to Claim 4, ~~characterized in that~~wherein wavelets, ~~preferably~~ "selected from the group consisting of biorthogonal" ~~or~~ " and second generation" wavelets ~~or~~and "lifting schemes" are used for the validity test.

~~6.~~17. ~~Method~~A method according to Claim 5, ~~characterized in that~~wherein coefficients of the ~~expected values for~~wavelets selected from the group consisting of approximation coefficients ~~or~~

~~the~~, and approximation coefficients and detailed coefficients ~~of the wavelets~~have expected values which are determined and compared at different resolutions.

~~7.~~18. ~~Method~~A method according to Claim 6, ~~characterized in that~~wherein the~~said~~ coefficients are determined in an estimator~~or~~.

19. A method according to Claim 6, wherein the coefficients are determined by means of a neuronal network.

~~8.~~20. ~~Danger~~A detector~~having means~~ for carrying out the method according to Claim 1, ~~having~~comprising at least one sensor ~~(2, 3, 4)~~ for sensing a danger parameter and ~~having~~ an electronic evaluation system ~~(1),~~ comprising a microprocessor~~(6),~~ for evaluating and analyzing ~~the~~ signals ~~of~~emitted ~~the~~from at least one sensor ~~(2, 3, 4), characterized in that~~wherein the microprocessor~~(6)~~ comprises a software program having a learning algorithm, based on multiple resolution, for analyzing the signals of the at least one sensor~~(2, 3, 4)~~.

~~9.~~21. ~~Danger~~A detector according to Claim 9, ~~characterized in that, on~~wherein the~~one hand, the said~~ sensor signals are analyzed by the learning algorithm for their ~~repeated or regular~~ occurrence and~~, on the other hand,~~ a validity test is carried out on the ~~result, and in that the~~analysis by a learning algorithm ~~for the validity test~~which uses wavelets~~, preferably "~~ selected from the group consisting of biorthogonal~~" or "~~ and second generation~~" wavelets~~ - - - - and lifting schemes.

~~10.~~22. ~~Danger~~A detector according to Claim 9, ~~characterized~~wherein in that the learning algorithm uses~~5~~ neuro-fuzzy methods.

~~11.~~23. ~~Danger~~A detector according to Claim 10, ~~characterized in that~~wherein the learning algorithm comprises~~the~~ two equations

$$f_m(x) = \sum \widehat{c}_{m,n} \cdot \varphi_{m,n}(x) \ (\Sigma \text{over all n's}) \text{ and}$$
$$\widehat{c}_{m,n}(k) = \sum \widetilde{\varphi}_{m,n}(x_i) \cdot y_i \,/ \sum \widetilde{\varphi}_{m,n}(x_i) \ (\Sigma \text{over all i's} = 1 \text{ to } k),$$

in which $\varphi_{m,n}$ denotes scaling functions, — ~~m,n~~ $\hat{c}_{m,n}$ denotes approximation coefficients and ~~Y_k~~ y_k denotes the k[th] input point of the neuronal network and $\widetilde{\varphi}_{m,n}$ is the dual function of $\varphi_{m,n}$.

ABSTRACT

The signals of a danger detector that has at least one sensor (2, 3, 4) for monitoring danger parameters and an electronic evaluation system (1) assigned to the at least one sensor (2, 3, 4) are compared with specified parameters. In addition, the signals are analyzed with regard to whether they occur increasingly frequently or regularly, and signals that occur~~in that signals occurring~~ increasingly frequently or regularly are classified as interference signals. The classification of signals as interference signals triggers an appropriate adjustment of the parameters. If interference signals occur, the validity of the result of the analysis of the signals of the at least one sensor (2, 3, 4) is checked prior to the adjustment of the parameters, and the parameters are adjusted as a function of the result of said validity test.

A danger detector having means for carrying out said method contains at least one sensor (2, 3, 4) for a danger parameter and an electronic evaluation system (1), comprising a microprocessor (6), for evaluating and analyzing the signals of the at least one sensor (2, 3, 4). The microprocessor (6) comprises a software program having a learning algorithm, based on multiple resolution, for analyzing the signals of the at least one sensor (2, 3,'4).

10/019562

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BAKER BOTTS LLP

Attorney Docket Number: A34703-PCT-USA

Title: METHOD FOR PROCESSING THE SIGNALS OF A DANGER DETECTOR AND DANGER DETECTOR HAVING MEANS FOR PERFORMING THE METHOD

Use Space Below for Additional Information:

Substitute Specification

10/019362
A34703-PCT-USA (070256.0214)
531 Rec'd PCT/PTO 25 OCT 2001
PATENT

BAKER BOTTS L.L.P

30 ROCKEFELLER PLAZA

NEW YORK, NEW YORK 10112

TO ALL WHOM IT MAY CONCERN:

Be it known that I, MARC PIERRE THUILLARD, citizen of Switzerland, whose post office address is Oeltrottenstrasse 5, CH-8707 Uetikon am See, Switzerland, have made an invention in:

METHOD FOR PROCESSING THE SIGNALS OF A DANGER DETECTOR AND DANGER DETECTOR HAVING MEANS FOR PERFORMING THE METHOD

of which the following is a

FIELD OF INVENTION

[0001] The present invention relates to a method for processing the signals of a danger detector that has at least one sensor for monitoring danger parameters and an electronic evaluation system that is assigned to the at least one sensor. The danger parameters are monitored by comparing the signals of the at least one sensor with specified parameters. The danger detector may be a smoke detector, a flame detector, a passive infrared detector, a microwave detector, a dual detector (passive infrared sensor + microwave sensor) or a noise detector.

BACKGROUND OF THE INVENTION

[0002] Modern danger detectors have achieved a sensitivity with regard to the detection of danger parameters that that the main problem is no longer the detection of a danger parameter as early as possible, but to distinguish reliably interference signals from true danger signals and thereby avoid false alarms. Danger signals and interference signals are distinguished substantially by using a plurality of different sensors and correlating their signals or by analyzing various features of the signals of a single sensor and/or by appropriate signal processing. A substantial improvement in interference immunity has already been achieved recently by using fuzzy logic.

[0003] Fuzzy logic is generally known. With regard to the evaluation of the signals of danger detectors, it is to be emphasized that signal values are allocated to fuzzy sets in accordance with a membership function. The value of the membership function, or the degree of membership of a fuzzy set, is between 0 and 1. It is important that the membership functions can be normalized, i.e. the sum of all the values of the membership function is equal to one, as a result of which the fuzzy logic evaluation permits an unambiguous interpretation of the signals.

SUMMARY OF THE PRESENT INVENTION

[0004] The object of the present invention is to provide a method for processing the signals of a danger detector that is further improved with regard to insensitivity to interference and interference immunity. The method according to the present invention is characterized in that the signals of the at least one sensor are analyzed on the basis of whether they occur increasingly frequently or regularly and in that signals occurring increasingly frequently or regularly are classified as interference signals. In a first

preferred embodiment of the method according to the present invention the classification of signals as interference signals triggers an appropriate adjustment of the parameters.

[0005] The method according to the present invention is based on the novel insight that a fire detector, for example, rarely if ever "sees" more than a few real fires between two inspections or two power failures, and that signals occurring increasingly frequently or regularly indicate the presence of sources of interference. The interference signals due to the interference sources are recognized as such and the detector parameters are adjusted accordingly. In this way, the detectors operated by the method according to the invention are capable of learning and are better able to distinguish between true danger signals and interference signals.

[0006] Another preferred embodiment of the method according to the present invention where interference signals occur, is that the validity of the result of the analysis of the signals of the at least one sensor is checked prior to the adjustment of the parameters, and the parameters are adjusted as a function of the result of this validity test. It is further preferred if the validity is tested by methods based on multiple resolution.

[0007] Yet another preferred embodiment of the method according to the present invention comprises using wavelets, preferably "biorthogonal" or "second generation" wavelets or "lifting schemes" for the validity test. The wavelet transformation is a transformation or imaging of a signal of the time domain into the frequency domain (see, for example, "The Fast Wavelet-Transform" by Mac A. Cody in Dr. Dobb's Journal, April 1992) and is therefore basically similar to the Fourier transformation or fast Fourier transformation. However, it differs from the latter in the basic function of the

transformation by which the signal is developed. In a Fourier transformation, a sine function and cosine function are used that are sharply localized in the frequency domain and indefinite in the time domain. In a wavelet transformation, a so-called wavelet or wave packet is used. Of the latter, there are various types, such as, for example, a Gauss, spline or hair wavelet that can each be displaced as desired in the time domain and expanded or compressed in the frequency domain by two parameters. Recently, novel wavelet methods have been disclosed that are often described as "second generation". Such wavelets are constructed using the so-called "lifting schemes" (Sweldens), which result in a series of approximations to the original signal, each of which has a coarser resolution than the preceding one. The number of operations necessary for the transformation is always proportional to the length of the original signal, whereas this number is disproportionate with respect to the signal length in the case of the Fourier transformation. The fast wavelet transformation can also be carried out inversely by restoring the original signal from the approximated values and coefficients for the reconstruction. The algorithm for resolving and reconstructing the signal and a table of resolving and reconstruction coefficients are given on the basis of an example for a spline wavelet in "An Introduction to Wavelets" by Charles K. Chui (Academic Press, San Diego, 1992); See also "A Wavelet Tour of Signal Processing" by S. Mallat (Academic Press, 1998).

[0008] In a further preferred embodiment of the method according to the present invention the expected values for the approximation coefficients, or the approximation coefficients and detailed coefficients of the wavelets, are determined and compared at

different resolutions. Preferably, the coefficients are determined in an estimator or by means of a neuronal network.

[0009] The present invention further relates to a danger detector having means for carrying out the aforesaid method, having at least one sensor for a danger parameter and an electronic evaluation system, comprising a microprocessor, for evaluating and analyzing the signals of the at least one sensor. The microprocessor comprises a software program having a learning algorithm, based on multiple resolution, for analyzing the signals of the at least one sensor.

[0010] In a preferred embodiment of the novel danger detector the sensor signals are analyzed by the learning algorithm for their repeated or regular occurrence, and a validity test is carried out on the result. The learning algorithm for the validity test uses wavelets, preferably "biorthogonal" or "second generation" wavelets. It is also preferred if the learning algorithm uses neuro-fuzzy methods.

[0011] In another preferred embodiment of the danger detector the learning algorithm comprises the following two equations:

$$f_m(x) = \sum \hat{c}_{m,n} \cdot \varphi_{m,n}(x) \ (\Sigma \text{ over all n's}) \text{ and}$$
$$\hat{c}_{m,n}(k) = \sum \tilde{\varphi}_{m,n}(x_i) \cdot y_i \, / \sum \tilde{\varphi}_{m,n}(x_i) \ (\Sigma \text{ over all i's} = 1 \text{ to k}),$$

in which $\varphi_{m,n}$ denotes wavelet scaling functions, $\hat{c}_{m,n}$ denotes approximation coefficients and y_k denotes the k[th] input point of the neuronal network, and $\tilde{\varphi}_{m,n}$ is the dual function of $\varphi_{m,n}$ (for definition of dual function see S. Mallat).

BRIEF DESCRIPTION OF THE DRAWINGS

[0012] The present invention is explained in greater detail below with reference to exemplary embodiments and the drawings, in which:

[0013] Figure 1 shows a function explanation diagram;

[0014] Figure 2 shows a block diagram of a danger detector equipped with means for carrying out the method according to the invention;

[0015] Figures 3a, 3b show two variants of a detail of the danger detector of Figure 2; and

[0016] Figure 4 shows a further variant of a detail of the danger detector of Figure 3.

DETAILED DESCRIPTION OF THE INVENTION

[0017] In accordance with the method of the present invention, the signals of a danger detector are processed in such a way that typical interference signals are detected and characterized. While fire detectors are predominantly mentioned in the present description, this in no way is intended to limit the scope of the invention and are but one of a number of detectors that have been chosen to exemplify the present invention. Hence the method according to the present invention is not restricted to fire detectors, and to the contrary, the method is suitable for danger detectors of all kinds, including intruder detectors and movement detectors.

[0018] Interference signals are analyzed by a simple and reliable method. Importantly, the interference signals are not only detected and characterized, but also the result of the analysis is checked. Wavelet theory and multiple resolution analysis (multi-resolution

analysis) are used. Depending on the result of the check, the detector parameters or the algorithms are adjusted. That means that the sensitivity is reduced or that certain automatic switchings between different sets of parameters are interlocked. By way of example, European Patent Application 99 122 975.8 describes a fire detector that has an optical sensor for scattered light, a temperature sensor and a fire gas sensor. The electronic evaluation system of the detector comprises a fuzzy controller in which the signals of the individual sensors are combined and the particular type of fire is diagnosed. A special application-specific algorithm is provided for each type of fire and can be selected on the basis of the diagnosis. In addition, the detector comprises various sets of parameters for personnel protection and property protection, between which on-line switching takes place under normal circumstances. If interference signals are diagnosed in the case of the temperature sensor and/or in the case of the fire gas sensor, the switching between these sets of parameters is interlocked.

[0019] If fuzzy logic is used, one of the problems to be solved is to translate the knowledge stored in a database into linguistically interpretable fuzzy rules. Neuro fuzzy methods developed for this purpose have not been convincing because they partly yield only fuzzy rules that are very difficult to interpret. On the other hand, so-called multiple resolution procedures offer a possibility of obtaining interpretable fuzzy rules. Their idea is to use a dictionary of membership functions that form a multiple resolution and to determine which are suitable membership functions for describing a control surface.

[0020] Figure 1 shows a diagram of such a multiple resolution. Row (a) shows the characteristic of a signal the amplitude of which varies in the ranges, small, medium and large. Correspondingly, row (b) shows the membership functions c1 "fairly small", c2

"medium" and c3 "rather large". These membership functions form a multiple resolution, which means that each membership function can be resolved into a sum of membership functions of a higher resolution level. This results in the membership functions c5 "very small", c6 "small to very small", c7 "very medium", c8 "large to very large" and c9 "very large" entered in row (c). In accordance with row (d), the triangular spline function c2 can therefore be converted into the sum of the translated triangle functions of the higher level of row (c).

[0021] In the Tagaki-Sugeno model, the fuzzy rules are expressed by the equation:

$$R_i : \text{if } x \text{ is } A_i, \text{then } y_i = f_i(x_i), \tag{1}$$

wherein A_i's are linguistic expressions, x is the linguistic input variable, and y is the output variable. The value of the linguistic input variables can be sharp or fuzzy. If, for example, x_i; is a linguistic variable for temperature, the value $\hat{x}$ may be a sharp number such as "30(°C)", or a fuzzy quantity such as "approximately 25(°C)", "approximately 25" being itself a fuzzy set. For a sharp input value, the output value of the fuzzy system is given by the equation:

$$\hat{y} = \sum \beta_i \cdot f(\hat{x}) / \sum \beta_i \tag{2}$$

where the degree of fulfillment β_i is given by the expression $\beta_i = \mu_{Ai}(\hat{X})$ in which $\mu_{Ai}(\hat{X})$ denotes the membership function of the linguistic term A_i. In many applications, a linear function is taken: $f(\hat{x}) = a^T i \cdot \hat{x} + b_i$. If a constant b_i is taken to describe the sharp output value y, the system becomes:

$$R_i : \text{if } x \text{ is } A_i \text{ then } y_i = b_i \tag{3}$$

[0022] If spline functions N^k are taken, for example as membership function $\mu_{Ai}(\hat{x}) = N^k[2^m(\hat{x} - n)]$, then the system of equation (3) is equivalent to

$$y_i = \sum b_i \cdot N^k[2^m(\hat{x} - n)] \tag{4}$$

[0023] In this special case, the output y is a linear sum of translated and expanded spline functions. This means that, given equation (4), the Tagaki-Sugeno model is equivalent to a multiple resolution spline model. It follows from this that wavelet procedures can be applied.

[0024] Figure 2 shows a block diagram of a danger detector equipped with a neuro-fuzzy learning algorithm. The detector denoted by the reference symbol M is, for example, a fire detector and has three sensors 2 to 4 for fire parameters. For example, an optical sensor 2 is provided for scattered light measurement or transmitted light measurement, a temperature sensor 3 and a fire gas sensor, for example a CO sensor, 4, are also provided. The output signals of the sensors 2 to 4 are fed to a processing stage 1 that has suitable means for processing the signals, such as, for example, amplifiers, and then are passed to a microprocessor or microcontroller denoted as μP 6.

[0025] In the μP 6, the sensor signals are compared both with one another and also individually with certain sets of parameters for the individual fire parameters. Of course, the number of sensors is not limited to three. Thus, only a single sensor may also be provided, and in this case, various characteristics, for example the signal gradient or the signal fluctuation, are extracted from the signal of the one sensor and investigated. Incorporated in the μP 6 are a neuro-fuzzy network 7 software and a validity test

(validation) 8. If the signal resulting from the neuro-fuzzy network 7 is regarded as an alarm signal, an appropriate alarm signal is fed to an alarm-emitting device 9 or to an alarm centre. If the validation 8 reveals that interference signals occur repeatedly or regularly, the sets of parameters stored in the μP 6 are correspondingly corrected.

[0026] The neuro-fuzzy network 7 is a series of neuronal networks which use the symmetrical scaling functions $\varphi_{m,n}(x) = \varphi_{m,n}(x) = \varphi[(x-n)\cdot 2^m]$ as an activation function. The scaling functions are such that $\{\varphi_{m,n}(x)\}$ form a multiple resolution. Each neuronal network uses activation functions of a given resolution. The m^{th} neuronal network optimizes the coefficients $\hat{c}_{m,n}$ with $f_m(x)$, the output of the m^{th} neuronal network.

$$f_m(x) = \sum \hat{c}_{m,n} \cdot \varphi_{m,n}(x) \quad (\Sigma \text{ over all n's}) \tag{5}$$

[0027] The coefficients $\hat{c}_{m,n}$ are calculated using the following equations:

$$\hat{c}_{m,n}(k) = \sum \tilde{\varphi}_{m,n}(x_i) \cdot y_i / \sum \tilde{\varphi}_{m,n}(x_i) \quad (\Sigma \text{ over all i's} = 1 \text{ to } k) \tag{6}$$

where $Y_k(x)$ is the k^{th} input point and $\tilde{\varphi}_{m,n}(x)$ is the dual function of $\varphi_{m,n}(x)$. The two equations (5) and (6) form the main algorithm of the neuro-fuzzy network.

[0028] In each iteration step, the values of the various neuronal networks are checked crosswise (validated), using the wavelet resolution, namely the one that the approximation coefficient $\hat{c}_{m,n}$ of a level m can be obtained from the approximation coefficients and wavelet coefficients of the level m-1 using the reconstruction algorithm or resolving algorithm.

[0029] In a preferred version, $\tilde{\varphi}_{m,n}(x)$ is a second-order spline function and $\varphi_{m,n}(x)$ is an interpolation function. In a second version, $\varphi_{m,n}(x)$ is a spline function and $\tilde{\varphi}_{m,n}(x)$ is the dual function of $\varphi_{m,n}(x)$. In a third version, $\tilde{\varphi}_{m,n}(x) = \varphi_{m,n}(x)$, where $\varphi_{m,n}(x)$ is the hair function. In these cases, it is possible to implement the learning algorithm in a simple microprocessor.

[0030] Figures 3a and 3b show two variants of a neuro-fuzzy network 7 and the associated validation stage 8. In Figure 3a, the input signal is approximated in various resolution stages as the weighted sum of wavelets $\Psi_{m,n}$ and scaling functions $\varphi_{m,n}$ having a given resolution. The validation stage 8 compares the approximation coefficients $\hat{c}_{m,n}$ with the approximation coefficients and detailed coefficients of the wavelets at the level of the next lower resolution stage. Wavelet reconstruction filter coefficients are denoted by p and q.

[0031] In the example of Figure 3b, the input signal is approximated in various resolution stages as a weighted sum of scaling functions $\varphi_{m,n}$ having a given resolution. The validation stage 8 compares the approximation coefficients $\hat{c}_{m,n}$ with the approximation coefficients at the next deeper resolution stage. Wavelet low-pass resolving coefficients are denoted by g.

[0032] The said coefficients can be determined in an estimator of the type shown in Figure 4 instead of in a neuro-fuzzy network 7. Said estimator is a so-called multiple resolution spline estimator that uses dual spline estimators based on the functions $\tilde{\varphi}_{m,n}(x)$ to estimate the coefficients $\hat{c}_{m,n}$ in the equation in the equation

$f_m(x) = \hat{c}_{m,n} \cdot \varphi_{m,n}(x)$. Wavelet spline estimators are used for adaptively determining the appropriate resolution for locally describing a basic hypersurface in an on-line learning process. A known estimator is the Nadaraya-Watson estimator with which the equation of the hypersurface f(x) is estimated using the following expression:

$$f(x) \sum_{k=1}^{k_{max}} K\left((x - x_k)/\lambda\right) \cdot y_k \Big/ \sum_{k=1}^{k_{max}} K\left((x - x_k)/\lambda\right). \tag{7}$$

[0033] Nadaraya-Watson estimators have two interesting characteristics they are estimators of the local mean quadratic deviation and it can be shown that they are so-called Bayes estimators of x_k, y_k in the case of a random design, where x_k, y_k are iid copies of a continuous random variable (X, Y).

[0034] The spline functions $\varphi(x)$ and their dual function $\tilde{\varphi}(x)$ can be used as estimators. We first use the function $\tilde{\varphi}(x)$ to estimate f(x) using $\lambda = 2^{-m}$ (m is an integer) from x_n, where $x_n \cdot 2^m \varepsilon Z$:

[0035] Using the symmetry of $\tilde{\varphi}(x)$, equation (6) for the dual spline function is equivalent to the use of an estimator centred at x_n:

$$\hat{f}(x_n) = \sum_{k=1}^{k_{max}} \tilde{\varphi}\left((x_k - x_n) \cdot 2^m\right) \cdot y_k \Big/ \sum_{k=1}^{k_{max}} \tilde{\varphi}\left((x_k - x_n) \cdot 2^m\right). \tag{8}$$

[0036] The expected value of the numerator in equation (7) is proportional to the approximation coefficients $c_{m,n}$. Equation (6) yields an estimate of $\hat{c}_{m,n}$ in $f_m(x)=\sum \hat{c}_{m,n} \cdot \varphi_{m,n}(x)$:

$$\hat{c}_{m,n} = \hat{f}(x_n). \tag{9}$$

[0037] In Figure 4, the available data (values) are denoted by a small square, their projection on dual spline functions by a small circle and the estimate on a regular grid by a small cross.

[0038] To validate the coefficient $\hat{c}_{,n}$, two conditions are necessary:

$$\left|\hat{c}_{m,n} - \sum_{p} g_{p-2n} \cdot \hat{c}_{m+1,p}\right| < \Delta \tag{10}$$

where the filter coefficients g correspond to the low-pass resolving coefficients for spline functions. In addition it is required that

$$\left| \sum_{k=1}^{k_{max}} \tilde{\varphi}\left((x_k - x_n) \cdot 2^m\right)\right| > T \tag{11}$$

so that divisions by very small values are prevented.

[0039] The strength of this method is that the calculation of a coefficient $\hat{c}_{m,n}$ requires the storage of only two values, the numerator and the denominator in equation (7). The method is therefore well suited for on-line learning using a simple microprocessor having low storage capacity.

[0040] The method can easily be adapted to density estimation by replacing equations (7) and (8) by the following equation:

$$\hat{c}_{m,n} = 1/k_{max} \cdot \sum_{k=1}^{k_{max}} \tilde{\varphi}_{m,n}(x_k) \cdot y_k \tag{12}$$

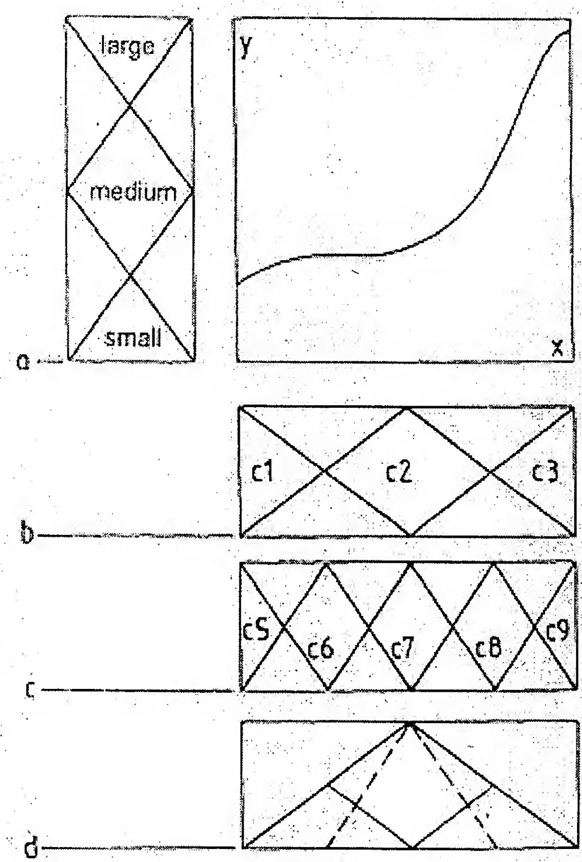
large
medium
small
y
x
a
b
c
d
c1
c2
c3
c5
c6
c7
c8
c9

FIG.1

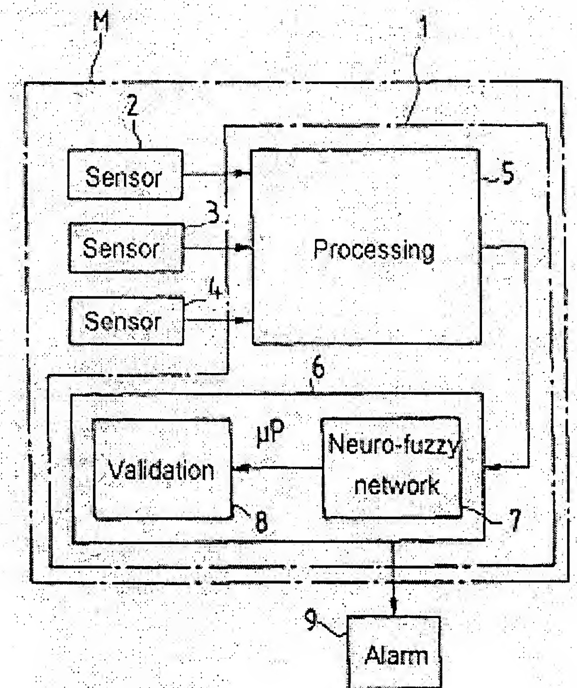
M
1
2
3
4
5
6
7
8
9
Sensor
Sensor
Sensor
Processing
μP
Validation
Neuro-fuzzy network
Alarm

FIG. 2

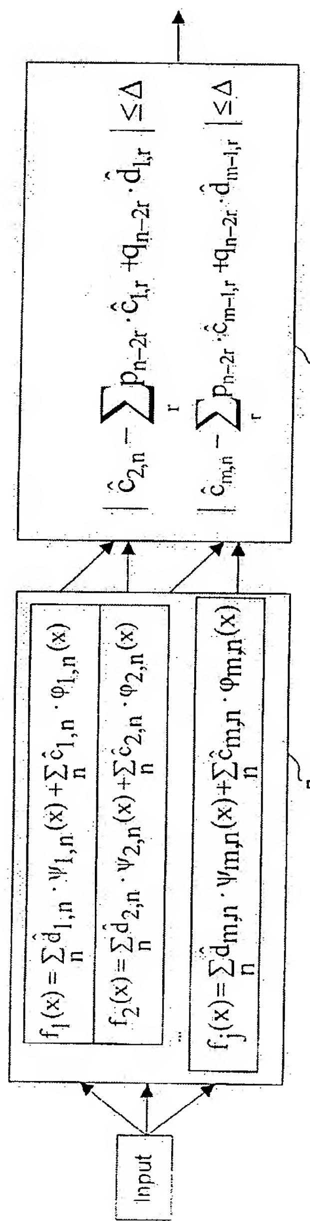
Input
$f_1(x) = \sum_n \hat{d}_{1,n} \cdot \psi_{1,n}(x) + \sum_n \hat{c}_{1,n} \cdot \varphi_{1,n}(x)$
$f_2(x) = \sum_n \hat{d}_{2,n} \cdot \psi_{2,n}(x) + \sum_n \hat{c}_{2,n} \cdot \varphi_{2,n}(x)$
$f_j(x) = \sum_n \hat{d}_{m,n} \cdot \psi_{m,n}(x) + \sum_n \hat{c}_{m,n} \cdot \varphi_{m,n}(x)$
7
$\left| \hat{c}_{2,n} - \sum_r p_{n-2r} \cdot \hat{c}_{1,r} + q_{n-2r} \cdot \hat{d}_{1,r} \right| \leq \Delta$
$\left| \hat{c}_{m,n} - \sum_r p_{n-2r} \cdot \hat{c}_{m-1,r} + q_{n-2r} \cdot \hat{d}_{m-1,r} \right| \leq \Delta$
8

FIG. 3a

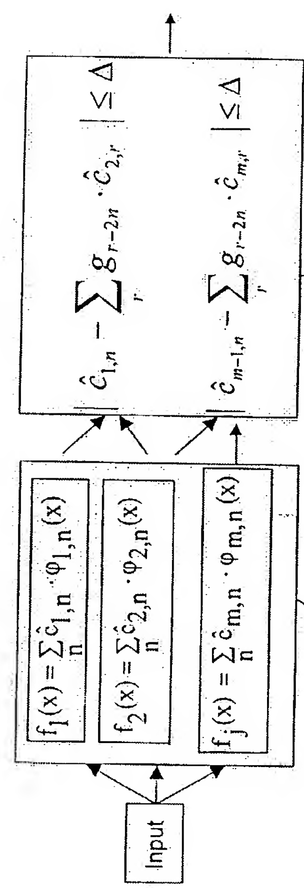
Input
$f_1(x) = \sum_n \hat{c}_{1,n} \cdot \varphi_{1,n}(x)$
$f_2(x) = \sum_n \hat{c}_{2,n} \cdot \varphi_{2,n}(x)$
$f_j(x) = \sum_n \hat{c}_{m,n} \cdot \varphi_{m,n}(x)$
7
$\left| \hat{c}_{1,n} - \sum_r g_{r-2n} \cdot \hat{c}_{2,r} \right| \leq \Delta$
$\left| \hat{c}_{m-1,n} - \sum_r g_{r-2n} \cdot \hat{c}_{m,r} \right| \leq \Delta$
8

FIG. 3b

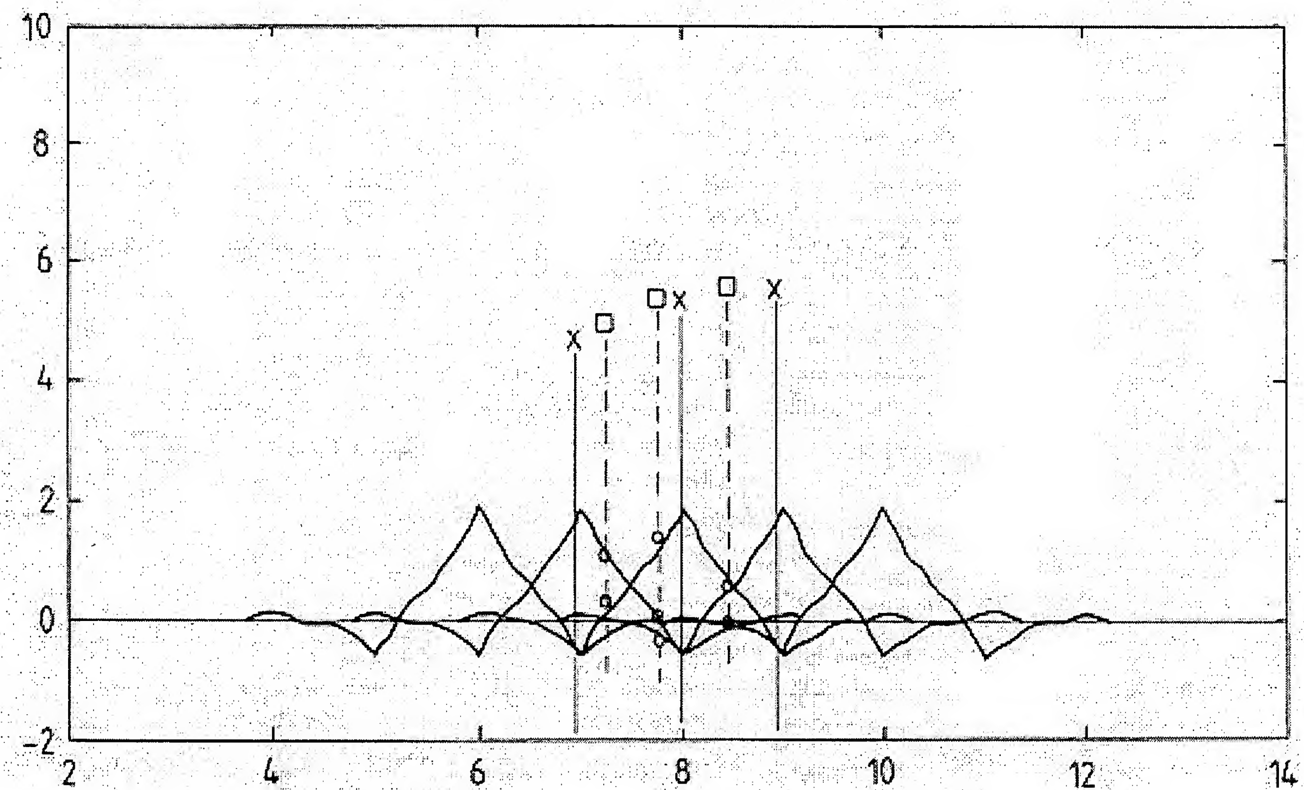

FIG. 4

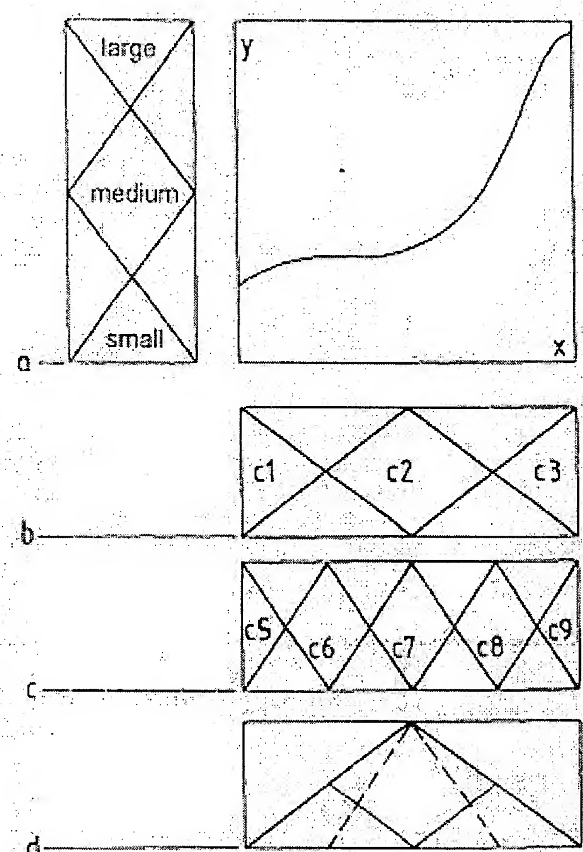

FIG.1

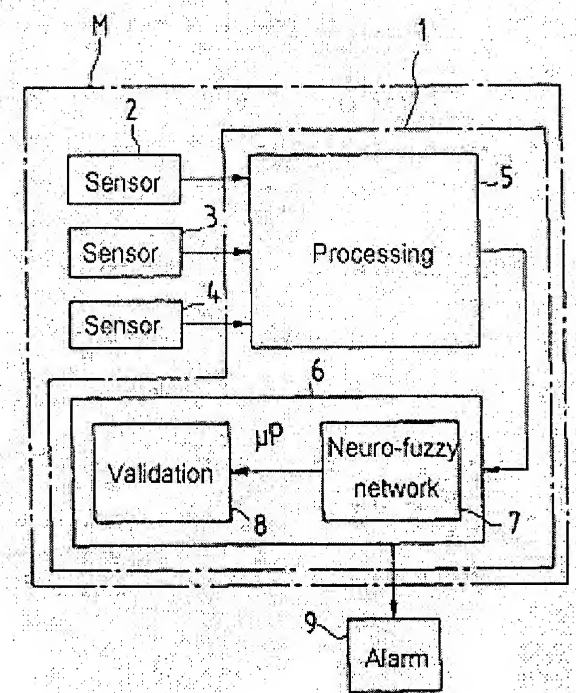

FIG. 2

10019362 .030603
10/019362

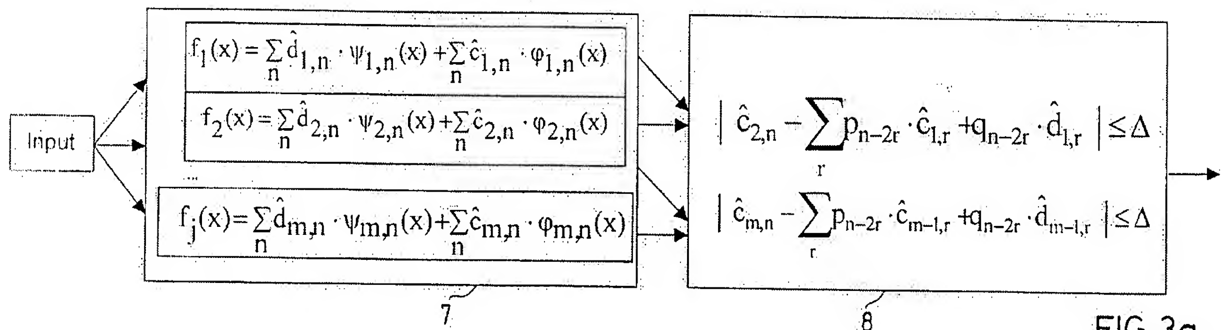
Input
$f_1(x)=\sum_n \hat{d}_{1,n}\cdot\psi_{1,n}(x)+\sum_n \hat{c}_{1,n}\cdot\varphi_{1,n}(x)$
$f_2(x)=\sum_n \hat{d}_{2,n}\cdot\psi_{2,n}(x)+\sum_n \hat{c}_{2,n}\cdot\varphi_{2,n}(x)$
$f_j(x)=\sum_n \hat{d}_{m,n}\cdot\psi_{m,n}(x)+\sum_n \hat{c}_{m,n}\cdot\varphi_{m,n}(x)$
7
$\left|\hat{c}_{2,n}-\sum_r p_{n-2r}\cdot\hat{c}_{1,r}+q_{n-2r}\cdot\hat{d}_{1,r}\right|\leq\Delta$
$\left|\hat{c}_{m,n}-\sum_r p_{n-2r}\cdot\hat{c}_{m-1,r}+q_{n-2r}\cdot\hat{d}_{m-1,r}\right|\leq\Delta$
8

FIG. 3a

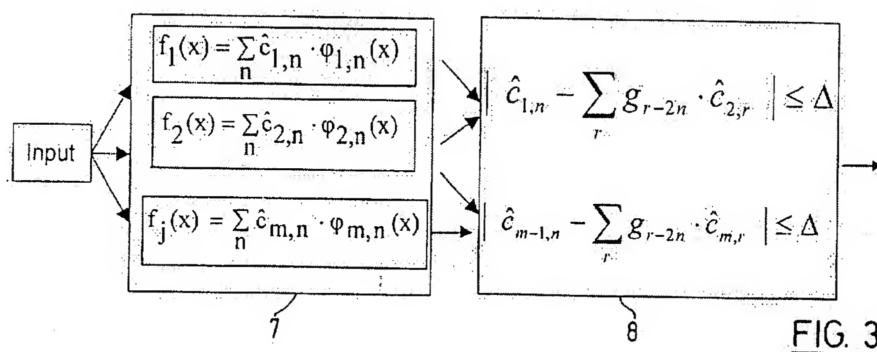
Input
$f_1(x)=\sum_n \hat{c}_{1,n}\cdot\varphi_{1,n}(x)$
$f_2(x)=\sum_n \hat{c}_{2,n}\cdot\varphi_{2,n}(x)$
$f_j(x)=\sum_n \hat{c}_{m,n}\cdot\varphi_{m,n}(x)$
7
$\left|\hat{c}_{1,n}-\sum_r g_{r-2n}\cdot\hat{c}_{2,r}\right|\leq\Delta$
$\left|\hat{c}_{m-1,n}-\sum_r g_{r-2n}\cdot\hat{c}_{m,r}\right|\leq\Delta$
8

FIG. 3b

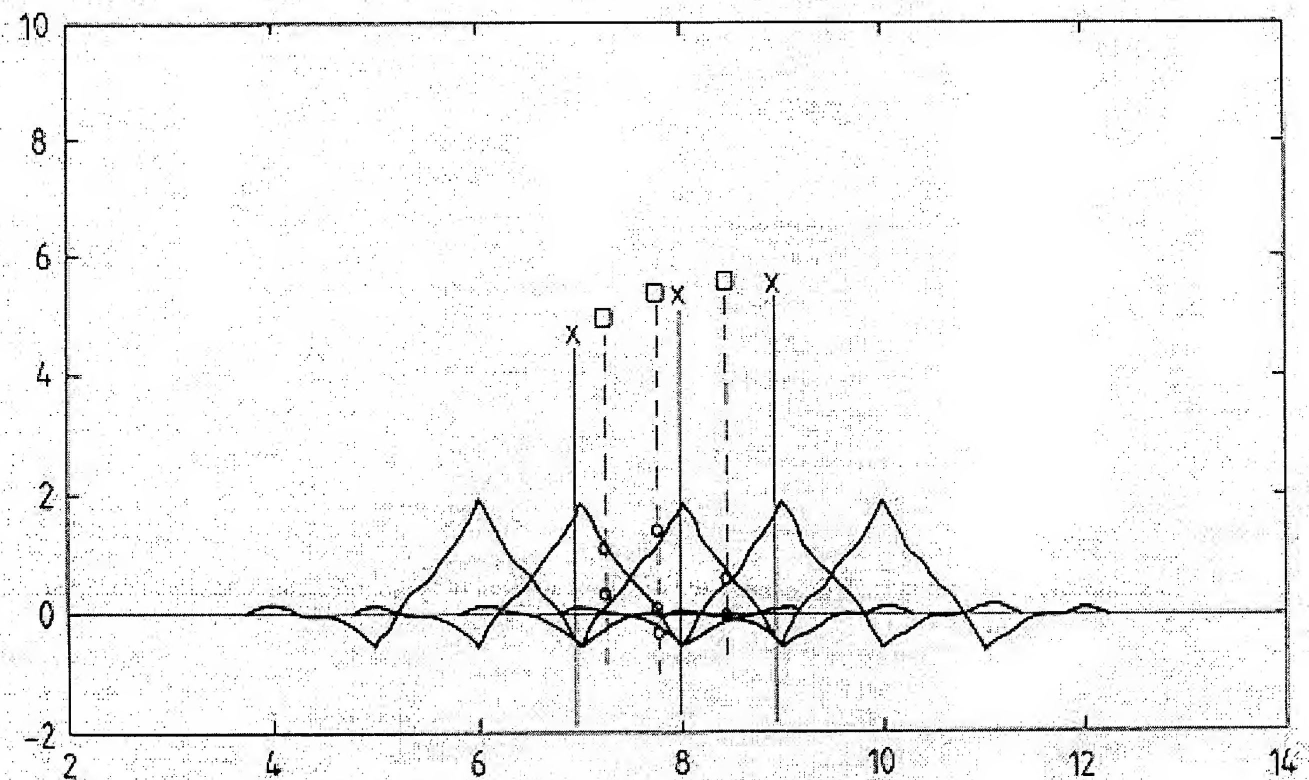

FIG. 4

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531 Rec'd PCT/PTO 25 OCT 2001

PATENT

BAKER BOTTS L.L.P

30 ROCKEFELLER PLAZA

NEW YORK, NEW YORK 10112

TO ALL WHOM IT MAY CONCERN:

Be it known that I, MARC PIERRE THUILLARD, citizen of Switzerland, whose post office address is Oeltrottenstrasse 5, CH-8707 Uetikon am See, Switzerland, have made an invention in:

METHOD FOR PROCESSING THE SIGNALS OF A DANGER DETECTOR AND DANGER DETECTOR HAVING MEANS FOR PERFORMING THE METHOD

~~DESCRIPTION~~

of which the following is a

FIELD OF INVENTION

[0001] The present invention relates to a method for processing the signals of a danger detector that has at least one sensor for monitoring danger parameters and an electronic evaluation system that is assigned to the at least one sensor~~, the~~. The danger parameters ~~being~~are monitored by comparing the signals of the at least one sensor with specified parameters. The danger detector may be ~~for example~~ a smoke detector, a flame detector, a passive infrared detector, a microwave detector, a dual detector (passive infrared sensor + microwave sensor) or a noise detector.

BACKGROUND OF THE INVENTION

[0002] Modern danger detectors have achieved a sensitivity with regard to the detection of danger parameters that ~~is such~~ that the main problem is no longer ~~to detect~~the detection of a danger parameter as early as possible, but to distinguish reliably interference signals from true danger signals ~~reliably~~ and thereby ~~to~~ avoid false alarms. Danger signals and interference signals are distinguished ~~in this connection~~ substantially by using a plurality of different sensors and correlating their signals or by analyzing various features of the signals of a single sensor and/or by appropriate signal processing~~,~~ ~~in which connection a~~. A substantial improvement in interference immunity has already been achieved recently by using fuzzy logic.

[0003] Fuzzy logic is generally known. With regard to the evaluation of the signals of danger detectors, it is to be emphasized that signal values are allocated to fuzzy sets in accordance with a membership function~~, the~~. The value of the membership function, or the degree of membership of a fuzzy set, ~~being~~is between 0 and 1. ~~Important in this connection~~ It is ~~the fact~~important that the membership functions can be normalized, i.e. the sum of all the values of the membership function is equal to one, as a result of which the fuzzy logic evaluation permits an unambiguous interpretation of the signals.

[0004] ~~The object of the present invention is now to specify a method of the type mentioned at the outset for processing the signals of a danger detector that is further improved with regard to insensitivity to interference and interference immunity.~~

SUMMARY OF THE PRESENT INVENTION

[0005] The object of the present invention is ~~now to specify a method of the type mentioned at the outset~~to provide a method for processing the signals of a danger detector

that is further improved with regard to insensitivity to interference and interference immunity. The method according to the present invention is characterized in that the signals of the at least one sensor are analyzed on the basis of whether they occur increasingly frequently or regularly and in that signals occurring increasingly frequently or regularly are classified as interference signals. In a first preferred embodiment~~A first preferred development~~ of the method according to the ~~invention is characterized in that~~present invention the classification of signals as interference signals triggers an appropriate adjustment of the parameters.

[0006] ~~A first preferred development of the method according to the invention is characterized in that the classification of signals as interference signals triggers an appropriate adjustment of the parameters.~~

[0007] The method according to the present invention is based on the novel insight that~~, for example,~~ a fire detector ~~never~~, for example, rarely if ever "sees" more than a few real fires between two inspections or two power failures, and that signals occurring increasingly frequently or regularly indicate the presence of sources of interference. The interference signals due to the interference sources are recognized as such and the detector parameters are adjusted accordingly. In this way, the detectors operated by the method according to the invention are capable of learning and are better able to distinguish between true danger signals and interference signals.

[0008] ~~A second~~Another preferred ~~development~~embodiment of the method according to the present invention ~~is characterized in that if~~where interference signals occur, is that the validity of the result of the analysis of the signals of the at least one sensor is checked prior to the adjustment of the parameters, and ~~in that~~ the parameters are adjusted as a

function of the result of this validity test. It is further preferred if~~A third preferred development is characterized in that~~ the validity is tested by methods based on multiple resolution.

[0009] ~~A third preferred development is characterized in that the validity is tested by methods based on multiple resolution.~~

[0010] ~~A fourth preferred development of the method according to the invention is characterized in that wavelets, preferably "biorthogonal" or "second generation" wavelets or "lifting schemes" are used for the validity test.~~

[0011] Yet another preferred embodiment~~A fourth preferred development~~ of the method according to the ~~invention is characterized in that~~present invention comprises using wavelets, preferably "biorthogonal" or "second generation" wavelets or "lifting schemes" ~~are used for the validity test.~~for the validity test. The wavelet transformation is a transformation or imaging of a signal of the time domain into the frequency domain (~~in this connection,~~ see, for example, "The Fast Wavelet-Transform" by Mac A. Cody in Dr. Dobb's Journal, April 1992)~~; it~~and is therefore basically similar to the Fourier transformation or fast Fourier transformation. However, it differs from the latter in the basic function of the transformation by which the signal is developed. In a Fourier transformation, a sine function and cosine function are used that are sharply localized in the frequency domain and indefinite in the time domain. In a wavelet transformation, a so-called wavelet or wave packet is used. Of the latter, there are various types, such as, for example, a Gauss, spline or hair wavelet that can each be displaced as desired in the time domain and expanded or compressed in the frequency domain by two parameters. Recently, novel wavelet methods have been disclosed that are often described as "second

generation". Such wavelets are constructed using the so-called "lifting schemes" (Sweldens)~~.~~, which result~~This results~~ in a series of approximations to the original signal, each of which has a coarser resolution than the preceding one. The number of operations necessary for the transformation is always proportional to the length of the original signal, whereas this number is disproportionate with respect to the signal length in the case of the Fourier transformation. The fast wavelet transformation can also be carried out inversely by restoring the original signal from the approximated values and coefficients for the reconstruction. The algorithm for resolving and reconstructing the signal and a table of resolving and reconstruction coefficients are given on the basis of an example for a spline wavelet in "An Introduction to Wavelets" by Charles K. Chui (Academic Press, San Diego, 1992)~~. On this topic see~~; See also "A Wavelet Tour of Signal Processing" by S. Mallat (Academic Press, 1998).

[0012] ~~This results in a series of approximations to the original signal, each of which has a coarser resolution than the preceding one. The number of operations necessary for the transformation is always proportional to the length of the original signal, whereas this number is disproportionate with respect to the signal length in the case of the Fourier transformation. The fast wavelet transformation can also be carried out inversely by restoring the original signal from the approximated values and coefficients for the reconstruction. The algorithm for resolving and reconstructing the signal and a table of resolving and reconstruction coefficients are given on the basis of an example for a spline wavelet in "An Introduction to Wavelets" by Charles K. Chui (Academic Press, San Diego, 1992). On this topic see also "A Wavelet Tour of Signal Processing" by S. Mallat (Academic Press, 1998).~~

[0013] ~~A~~In a further preferred ~~development~~embodiment of the method according to the present invention ~~is characterized in that~~ the expected values for the approximation coefficients, or the approximation coefficients and detailed coefficients of the wavelets, are determined and compared at different resolutions. Preferably, the ~~said~~ coefficients are determined in an estimator or by means of a neuronal network.

[0014] The present invention ~~furthermore~~further relates to a danger detector having means for carrying out the ~~said~~aforesaid method, having at least one sensor for a danger parameter and ~~having~~ an electronic evaluation system, comprising a microprocessor, for evaluating and analyzing the signals of the at least one sensor. The~~The danger detector according to the invention is characterized in that the~~ microprocessor comprises a software program having a learning algorithm, based on multiple resolution, for analyzing the signals of the at least one sensor.

[0015] ~~The danger detector according to the invention is characterized in that the microprocessor comprises a software program having a learning algorithm, based on multiple resolution, for analyzing the signals of the at least one sensor.~~

[0016] ~~A~~In ~~first~~a preferred embodiment of the novel danger detector ~~according to~~ the ~~invention is characterized in that, on the one hand, the said~~ sensor signals are analyzed by the learning algorithm for their repeated or regular occurrence, and~~, on the other hand,~~ a validity test is carried out on the result~~, and in that the~~. The learning algorithm for the validity test uses wavelets, preferably "biorthogonal" or "second generation" wavelets. It is also preferred if~~A second preferred embodiment of the danger detector according to the invention is characterized in that~~ the learning algorithm uses neuro-fuzzy methods.

[0017] ~~A second preferred embodiment of the danger detector according to the invention is characterized in that the learning algorithm uses neuro-fuzzy methods.~~

[0018] ~~A~~In ~~third~~another preferred embodiment of the danger detector ~~according to the invention is characterized in that~~ the learning algorithm comprises the following two equations:

$$f_m(x)=\sum \hat{c}_{m,n} \cdot \varphi_{m,n}(x)\ (\textstyle\sum \text{over all n's}) \text{ and}$$
$$\hat{c}_{m,n}(k)=\sum \tilde{\varphi}_{m,n}(x_i)\cdot y_i / \sum \tilde{\varphi}_{m,n}(x_i)\ (\textstyle\sum \text{over all i's} = 1 \text{ to k}),$$

in which ~~,~~ $\varphi_{m,n}$ denotes wavelet scaling functions, ~~,~~ $\hat{c}_{m,n}$ denotes approximation coefficients and ~~Y_K~~y_k denotes the ~~K^{th}~~k^{th} input point of the neuronal network, and $\tilde{\varphi}_{m,n}$ is the dual function of $\varphi_{m,n}$ (for definition of dual function see S. Mallat).

BRIEF DESCRIPTION OF THE DRAWINGS

[0019] The present invention is explained in greater detail below with reference to exemplary embodiments and the drawings;, in ~~the drawings~~which:

[0020] Figure 1 shows a function explanation diagram~~,~~;

[0021] Figure 2 shows a block diagram of a danger detector equipped with means for carrying out the method according to the invention~~,~~;

~~carrying out the method according to the invention,~~

[0022] Figures 3a, 3b show two variants of a detail of the danger detector of Figure 2; and

[0023] Figure 4 shows a further variant of a detail of the danger detector of Figure 3.

DETAILED DESCRIPTION OF THE INVENTION

[0024] ~~The~~In accordance with the method ~~according to~~of the present invention ~~processes~~, the signals of a danger detector are processed in such a way that typical interference signals are detected and characterized. ~~If~~ While fire detectors are predominantly mentioned in ~~a~~the present description, this ~~does not mean~~in no way is intended to limit the scope of the invention and are but one of a number of detectors that have been chosen to exemplify the present invention. Hence the method according to the present invention is not restricted to fire detectors~~. On~~, and to the contrary, the method is suitable for danger detectors of all kinds, ~~in particular also for~~including intruder detectors and movement detectors.

~~The interference signals mentioned are analyzed by a simple and reliable method. An important feature of this method is that the interference signals are not only detected and characterized, but that the result of the analysis is checked. Wavelet theory and multiple resolution analysis (multiresolution analysis) are used. Depending on the result of the check, the detector parameters or the algorithms are adjusted. That means that, for example, the sensitivity is reduced or that certain automatic switchings between different sets of parameters are interlocked.~~

[0025] ~~The latter may be explained by means of an~~Interference signals~~The interference signals mentioned~~ are analyzed by a simple and reliable method. ~~An important feature of this method is that~~Importantly, the interference signals are not only detected and

characterized, but ~~that~~ also the result of the analysis is checked. Wavelet theory and multiple resolution analysis (~~multiresolution~~multi-resolution analysis) are used. Depending on the result of the check, the detector parameters or the algorithms are adjusted. That means that~~, for example,~~ the sensitivity is reduced or that certain automatic switchings between different sets of parameters are interlocked. By way of example~~:~~, European Patent Application 99 122 ~~25-~~975.8 describes a fire detector that has an optical sensor for scattered light, a temperature sensor and a fire gas sensor. The electronic evaluation system of the detector comprises a fuzzy controller in which the signals of the individual sensors are combined and the particular type of fire is diagnosed. A special application-specific algorithm is provided for each type of fire and can be selected on the basis of the diagnosis. In addition, the detector comprises various sets of parameters for personnel protection and property protection, between which on-line switching takes place under normal circumstances. If interference signals are ~~now~~ diagnosed in the case of the temperature sensor and/or in the case of the fire gas sensor, the switching between these sets of parameters is interlocked.

[0026] If fuzzy logic is used, one of the problems to be solved is to translate the knowledge stored in a database into linguistically interpretable fuzzy rules. Neuro fuzzy methods developed for this purpose have not been convincing because they partly yield only fuzzy rules that are very difficult to interpret. On the other hand, so-called multiple resolution procedures offer a possibility of obtaining interpretable fuzzy rules. Their idea is to use a dictionary of membership functions that form a multiple resolution and to determine which are suitable membership functions for describing a control surface.

[0027] Figure 1 shows a diagram of such a multiple resolution. Row (a) shows the characteristic of a signal ~~whose~~the amplitude of which varies in the ranges, small, medium and large. Correspondingly, row (b) shows the membership functions c1 "fairly small", c2 "medium" and c3 "rather large". These membership functions form a multiple resolution, which means that each membership function can be resolved into a sum of membership functions of a higher resolution level. This results in the membership functions c5 "very small", c6 "small to very small", c7 "very medium", c8 "large to very large" and c9 "very large" entered in row (c). In accordance with row (d), the triangular spline function c2 can therefore be converted~~, for example~~ into the sum of the translated triangle functions of the higher level of row (c).

[0028] In the Tagaki-Sugeno model, the fuzzy rules are expressed by the equation:

R_i :if x is A_i, then $y_i = f_i(x_i)$, ~~R_j: if x is A_j, then $y_i = f_i(x_i)$~~ (1)

~~Here~~wherein A_i's are linguistic expressions, x is the linguistic input variable, and y is the output variable. The value of the linguistic input variables can be sharp or fuzzy. If, for example, ~~x~~ x_i; is a linguistic variable for temperature, the value $\hat{x}$ may be a sharp number such as "30(°C)", or a fuzzy quantity such as "approximately 25(°C)", "approximately 25" being itself a fuzzy set. For a sharp input value, the output value of the fuzzy system is given by the equation:

$$\hat{y} = \sum \beta_i \cdot f(\hat{x}) / \sum \beta_i \qquad (2)$$

where the degree of fulfillment ; β_i is given by the expression $\beta_i = \mu_{Ai}(\hat{X})$ in which $\mu_{Ai}(\hat{X})$ denotes the membership function of the linguistic term A_i. In many applications,

a linear function is taken: $f(\hat{x}) = a^T i \cdot \hat{x} + b_i$. If a constant b_i is taken to describe the sharp output value y, the system becomes:

$$\cancel{R_i: \text{if } x \text{ is } A_i \text{ then } y_i = b_i}\ R_i : \text{if } x \text{ is } A_i \text{ then } y_i = b_i \tag{3}$$

[0029] If spline functions N^k are taken, for example as membership function ~~then the system of equation (3) is equivalent to~~ $\mu_{Ai}(\hat{x}) = N^k[2^m(\hat{x} - n)]$, then the system of equation (3) is equivalent to

$$y_i = \sum b_i \cdot N^k[2^m(\hat{x} - n)] \tag{4}$$

[0030] In this special case, the output y is a linear sum of translated and expanded spline functions. ~~And that~~This means that, given equation (4), the Tagaki-Sugeno model is equivalent to a multiple resolution spline model. ~~And it~~ It follows from this that wavelet procedures can be applied.

[0031] Figure 2 shows a block diagram of a danger detector equipped with a neuro-fuzzy learning algorithm. The detector denoted by the reference symbol M is, for example, a fire detector and has three sensors 2 to 4 for fire parameters. For example, an optical sensor 2 is provided for scattered light measurement or transmitted light measurement, a temperature sensor 3 and a fire gas sensor, for example a CO sensor, 4, are also provided. The output signals of the sensors 2 to 4 are fed to a processing stage 1 that has suitable means for processing the signals, such as, for example, amplifiers, and then are passed ~~from the latter~~ to a microprocessor or microcontroller denoted ~~below~~ as µP 6.

[0032] In the µP 6, the sensor signals are compared both with one another and also individually with certain sets of parameters for the individual fire parameters. Of course, the number of sensors is not limited to three. Thus, only a single sensor may also be provided, and in this case, various characteristics, for example the signal gradient or the signal fluctuation, are extracted from the signal of the one sensor and investigated. Incorporated in the µP 6 are a neuro-fuzzy network 7 software and a validity test (validation) 8. If the signal resulting from the neuro-fuzzy network 7 is regarded as an alarm signal, an appropriate alarm signal is fed to an alarm-emitting device 9 or to an alarm centre. If the validation 8 reveals that interference signals occur repeatedly or regularly, the sets of parameters stored in the µP 6 are correspondingly corrected.

[0033] The neuro-fuzzy network 7 is a series of neuronal networks which use the symmetrical scaling functions $\varphi_{m,n}(x) = \varphi_{m,n}(x) = \varphi[(x-n)\cdot 2^m]$ as an activation function. The scaling functions are such that ~~{} form a multiple resolution. Each neuronal network uses activation functions of a given resolution. The m^{th} neuronal network optimizes the coefficients , with $f_m(X)$, the output of the m^{th} neuronal network.~~ $\{\varphi_{m,n}(x)\}$ ~~}~~ form a multiple resolution. Each neuronal network uses activation functions of a given resolution. The m^{th} neuronal network optimizes the coefficients $\hat{c}_{m,n}$ with $f_m(x)$, ~~, with $f_m(X)$,~~ the output of the m^{th} neuronal network.

$$f_m(x) = \sum \hat{c}_{m,n} \cdot \varphi_{m,n}(x) \quad (\Sigma \text{ over all n's}) \tag{5}$$

[0034] The coefficients ~~The coefficients~~ $\hat{c}_{m,n}$ are calculated using the following equations:

$$\hat{c}_{m,n}(k) = \sum \tilde{\varphi}_{m,n}(x_i) \cdot y_i / \sum \tilde{\varphi}_{m,n}(x_i) \quad (\Sigma \text{ over all i's} = 1 \text{ to } k) \tag{6}$$

where $Y_k(x)$ is the ~~k'''~~ k^{th} input point and $\tilde{\varphi}_{m,n}(x)$ is the dual function of $\varphi_{m,n}(x)$. The two equations (5) and (6) form the main algorithm of the neuro-fuzzy network.

[0035] In each iteration step, the values of the various neuronal networks are checked crosswise (validated), ~~for which purpose a characteristic of~~using the wavelet resolution ~~is used~~, namely the one that the approximation coefficient ~~of a level m can be obtained from the approximation coefficients and wavelet coefficients of the level m-1 using the reconstruction algorithm or resolving algorithm.~~ $\hat{c}_{m,n}$ of a level m can be obtained from the approximation coefficients and wavelet coefficients of the level m-1 using the reconstruction algorithm or resolving algorithm.

[0036] In a preferred version, $\tilde{\varphi}_{m,n}(x)$ is a second-order spline function and $\varphi_{m,n}(x)$ is an interpolation function. In a second version, $\varphi_{m,n}(x)$ is a spline function and $\tilde{\varphi}_{m,n}(x)$ is the dual function of $\varphi_{m,n}(x)$. In a third version, $\tilde{\varphi}_{m,n}(x) = \varphi_{m,n}(x)$, where ~~In a preferred version, is a second-order spline function and is an interpolation function. In a second version, is a spline function and is the dual function of . In a third version, where~~ $\varphi_{m,n}(x)$ is the hair function. In these cases, it is possible to implement the learning algorithm in a simple microprocessor.

[0037] Figures 3a and 3b show two variants of a neuro-fuzzy network 7 and the associated validation stage 8. In ~~the example of~~ Figure 3a, the input signal is approximated in various resolution stages as the weighted sum of wavelets $\Psi_{m,n}$ and scaling functions ~~having a given resolution. The validation stage 8 compares the~~

~~approximation coefficients with the approximation coefficients and detailed coefficients of the wavelets at the level of the next lower resolution stage. Wavelet reconstruction filter coefficients are denoted by p and q.~~ $\varphi_{m,n}$ having a given resolution. The validation stage 8 compares the approximation coefficients $\hat{c}_{m,n}$ with the approximation coefficients and detailed coefficients of the wavelets at the level of the next lower resolution stage. Wavelet reconstruction filter coefficients are denoted by p and q.

[0038] In the example of Figure 3b, the input signal is approximated in various resolution stages as a weighted sum of scaling functions $\varphi_{m,n}$ having a given resolution. The validation stage 8 compares the approximation coefficients ~~with the approximation coefficients at the next deeper resolution stage. Wavelet low-pass resolving coefficients are denoted by g.~~ $\hat{c}_{m,n}$ with the approximation coefficients at the next deeper resolution stage. Wavelet low-pass resolving coefficients are denoted by g.

[0039] The said coefficients can be determined in an estimator of the type shown in Figure 4 instead of in a neuro-fuzzy network 7. Said estimator is a so-called multiple resolution spline estimator that uses dual spline estimators based on the functions $\tilde{\varphi}_{m,n}(x)$ to estimate the coefficients ~~in the equation~~ $\hat{c}_{m,n}$ in the equation in the equation ~~The said coefficients can be determined in an estimator of the type shown in Figure 4 instead of in a neuro-fuzzy network 7. Said estimator is a so-called multiple resolution spline estimator that uses dual spline estimators based on the functions to estimate the coefficients in the equation~~ $f_m(x) = \hat{c}_{m,n} \cdot \varphi_{m,n}(x)$. ~~in the equation .~~ Wavelet spline estimators are used for adaptively determining the appropriate resolution for locally

describing a basic hypersurface in an on-line learning process. A known estimator is the Nadaraya-Watson estimator with which the equation of the hypersurface f(x) is estimated using the following expression:

$$f(x) \sum_{k=1}^{k_{max}} K\left((x - x_k)/\lambda\right) \cdot y_k \Big/ \sum_{k=1}^{k_{max}} K\left((x - x_k)/\lambda\right). \qquad (\cancel{6}7)$$

[0040] Nadaraya-Watson estimators have two interesting characteristics they are estimators of the local mean quadratic deviation and it can be shown that they are so-called Bayes estimators of ~~(X^k, Y^k) in the case of a random design, where (X^k, Y^k) are iid copies of a continuous random variable (X, Y).~~ x_k, y_k ~~(X^k, Y^k)~~ in the case of a random design, where ~~(X^k, Y^k)~~ x_k, y_k are iid copies of a continuous random variable (X, Y).

[0041] The spline functions $\varphi(x)$ and their dual function ~~The spline functions and their dual function~~ $\tilde{\varphi}(x)$ can be used as estimators. We first use the function ~~to estimate f(x) using $\lambda = 2^{-m}$ (m is an integer) from X_n, where $X_n \cdot 2^m$ & Z:~~ $\tilde{\varphi}(x)$ to estimate f(x) using $\lambda = 2^{-m}$ (m is an integer) from x_n, where $x_n \cdot 2^m \varepsilon Z$:

[0042] Using the symmetry of $\tilde{\varphi}(x)$, equation (6) for the dual spline function is equivalent to the use of an estimator centred at ~~X_n:~~ x_n :

$$\hat{f}(x_n) = \sum_{k=1}^{k_{max}} \tilde{\varphi}\left((x_k - x_n) \cdot 2^m\right) \cdot y_k \Big/ \sum_{k=1}^{k_{max}} \tilde{\varphi}\left((x_k - x_n) \cdot 2^m\right). \qquad \cancel{(7)}(8)$$

The expected value of the numerator in equation (7) is proportional to the approximation coefficients ~~$C_{m,n}$. Equation (6) yields an estimate of $_{m,n}$ in $f_m(x)$ =~~

[0043] ~~(8)~~ $c_{m,n}$. ~~$C_{m,n}$.~~ Equation (6) yields an estimate of ~~$_{m,n}$ in $f_m(x)$ =~~

$\hat{c}_{m,n}$ in $f_m(x) = \sum \hat{c}_{m,n} \cdot \varphi_{m,n}(x)$:

$$\hat{c}_{m,n} = \hat{f}(x_n). \quad (9)$$

[0044] In Figure 4, the available data (values) are denoted by a small square, their projection on dual spline functions by a small circle and the estimate on a regular grid by a small cross.

[0045] To validate the coefficient ~~,~~ $\hat{c}_{,n}$, two conditions are necessary:

$$\left| \hat{c}_{m,n} - \sum_p g_{p-2n} \cdot \hat{c}_{m+1,p} \right| < \Delta \qquad (\cancel{9}10)$$

where the filter coefficients g correspond to the low-pass resolving coefficients for spline functions. In addition it is required that

$$\left| \sum_{k=1}^{k_{max}} \tilde{\varphi}\left((x_k - x_n) \cdot 2^m\right) \right| > T \qquad (\cancel{10}11)$$

so that divisions by very small values are prevented.

[0046] The strength of this method is that the calculation of a coefficient ~~The strength of this method is that the calculation of a coefficient~~ $\hat{c}_{m,n}$ requires the storage of only two

[redacted]

values, the numerator and the denominator in equation (7). The method is therefore well suited for on-line learning using a simple microprocessor having low storage capacity.

[0047] The method can easily be adapted to density estimation by replacing equations (7) and (8) by the following equation:

$$\hat{c}_{m,n} = 1/k_{max} \cdot \sum_{k=1}^{k_{max}} \tilde{\varphi}_{m,n}(x_k) \cdot y_k \qquad (\cancel{11}12)$$

Method for processing the signals of a danger detector and danger detector having means for performing the method

Description

The present invention relates to a method for processing the signals of a danger detector that has at least one sensor for monitoring danger parameters and an electronic evaluation system that is assigned to the at least one sensor, the danger parameters being monitored by comparing the signals of the at least one sensor with specified parameters. The danger detector may be for example a smoke detector, a flame detector, a passive infrared detector, a microwave detector, a dual detector (passive infrared sensor + microwave sensor) or a noise detector.

Modern danger detectors have achieved a sensitivity with regard to the detection of danger parameters that is such that the main problem is no longer to detect a danger parameter as early as possible, but to distinguish interference signals from true danger signals reliably and thereby to avoid false alarms. Danger signals and interference signals are distinguished in this connection substantially by using a plurality of different sensors and correlating their signals or by analysing various features of the signals of a single sensor and/or by appropriate signal processing, in which connection a substantial improvement in interference immunity has already been achieved recently by using fuzzy logic.

Fuzzy logic is generally known. With regard to the evaluation of the signals of danger detectors, it is to be emphasized that signal values are allocated to fuzzy sets in accordance with a membership function, the value of the membership function, or the degree of membership of a fuzzy set, being between 0 and 1. Important in this connection is the fact that the membership functions can be normalized, i.e. the sum of all the values of the membership function is equal to one, as a result of which the fuzzy logic evaluation permits an unambiguous interpretation of the signals.

The object of the present invention is now to specify a method of the type mentioned at the outset for processing the signals of a danger detector that is further improved with regard to insensitivity to interference and interference immunity.

The method according to the invention is characterized in that the signals of the at least one sensor are analysed on the basis of whether they occur increasingly frequently or regularly and in that signals occurring increasingly frequently or regularly are classified as interference signals.

A first preferred development of the method according to the invention is characterized in that the classification of signals as interference signals triggers an appropriate adjustment of the parameters.

The method according to the invention is based on the novel insight that, for example, a fire detector never "sees" more than a few real fires between two inspections or two power failures and that signals occurring increasingly frequently or regularly indicate the presence of sources of interference. The interference signals due to the interference sources are recognized as such and the detector parameters are adjusted accordingly. In this way, the detectors operated by the method according to the invention are capable of learning and are better able to distinguish between true danger signals and interference signals.

A second preferred development of the method according to the invention is characterized in that if interference signals occur, the validity of the result of the analysis of the signals of the at least one sensor is checked prior to the adjustment of the parameters and in that the parameters are adjusted as a function of the result of this validity test.

A third preferred development is characterized in that the validity is tested by methods based on multiple resolution.

A fourth preferred development of the method according to the invention is characterized in that wavelets, preferably "biorthogonal" or "second generation" wavelets or "lifting schemes" are used for the validity test.

The wavelet transformation is a transformation or imaging of a signal of the time domain into the frequency domain (in this connection, see, for example, "The Fast Wavelet-Transform" by Mac A. Cody in Dr. Dobb's Journal, April 1992); it is therefore basically similar to the Fourier transformation or fast Fourier transformation. However, it differs from the latter in the basic function of the transformation by which the signal is developed. In a Fourier transformation, a sine function and cosine function are used that are sharply localized in the frequency domain and indefinite in the time domain. In a wavelet transformation, a so-called wavelet or wave packet is used. Of the latter, there are various types, such as, for example, a Gauss, spline or hair wavelet that can each be displaced as desired in the time domain and expanded or compressed in the frequency domain by two parameters. Recently, novel wavelet methods have been disclosed that are often described as "second generation". Such wavelets are constructed using the so-called "lifting schemes" (Sweldens).

This results in a series of approximations to the original signal, each of which has a coarser resolution than the preceding one. The number of operations necessary for the transformation is

always proportional to the length of the original signal, whereas this number is disproportionate with respect to the signal length in the case of the Fourier transformation. The fast wavelet transformation can also be carried out inversely by restoring the original signal from the approximated values and coefficients for the reconstruction. The algorithm for resolving and reconstructing the signal and a table of resolving and reconstruction coefficients are given on the basis of an example for a spline wavelet in "An Introduction to Wavelets" by Charles K. Chui (Academic Press, San Diego, 1992). On this topic see also "A Wavelet Tour of Signal Processing" by S. Mallat (Academic Press, 1998).

A further preferred development of the method according to the invention is characterized in that the expected values for the approximation coefficients or the approximation coefficients and detailed coefficients of the wavelets are determined and compared at different resolutions. Preferably, the said coefficients are determined in an estimator or by means of a neuronal network.

The invention furthermore relates to a danger detector having means for carrying out the said method, having at least one sensor for a danger parameter and having an electronic evaluation system, comprising a microprocessor, for evaluating and analysing the signals of the at least one sensor.

The danger detector according to the invention is characterized in that the microprocessor comprises a software program having a learning algorithm, based on multiple resolution, for analysing the signals of the at least one sensor.

A first preferred embodiment of the danger detector according to the invention is characterized in that, on the one hand, the said sensor signals are analysed by the learning algorithm for their repeated or regular occurrence and, on the other hand, a validity test is carried out on the result, and in that the learning algorithm for the validity test uses wavelets, preferably "biorthogonal" or "second generation" wavelets.

A second preferred embodiment of the danger detector according to the invention is characterized in that the learning algorithm uses neuro-fuzzy methods.

A third preferred embodiment of the danger detector according to the invention is characterized in that the learning algorithm comprises the two equations

$f_m(x) = \sum \hat{c}_{m,n} \cdot \varphi_{m,n}(x)$ (Σ over all n's) and

$\hat{c}_{m,n}(k) = \sum \tilde{\varphi}_{m,n}(x_i) \cdot y_i / \sum \tilde{\varphi}_{m,n}(x_i)$ (Σ over all i's = 1 to k)

in which $\varphi_{m,n}$ denotes wavelet scaling functions, $\hat{c}_{m,n}$ denotes approximation coefficients and y_k denotes the k^{th} input point of the neuronal network and $\tilde{\varphi}_{m,n}$ is the dual function of $\varphi_{m,n}$ (for definition of dual function see S. Mallat).

The invention is explained in greater detail below with reference to exemplary embodiments and the drawings; in the drawings:

Figure 1 shows a function explanation diagram,

Figure 2 shows a block diagram of a danger detector equipped with means for carrying out the method according to the invention,

Figures 3a, 3b show two variants of a detail of the danger detector of Figure 2; and

Figure 4 shows a further variant of a detail of the danger detector of Figure 3.

The method according to the invention processes the signals of a danger detector in such a way that typical interference signals are detected and characterized. If fire detectors are predominantly mentioned in a present description, this does not mean that the method according to the invention is restricted to fire detectors. On the contrary, the method is suitable for danger detectors of all kinds, in particular also for intruder detectors and movement detectors.

The interference signals mentioned are analysed by a simple and reliable method. An important feature of this method is that the interference signals are not only detected and characterized, but that the result of the analysis is checked. Wavelet theory and multiple resolution analysis (multiresolution analysis) are used. Depending on the result of the check, the detector parameters or the algorithms are adjusted. That means that, for example, the sensitivity is reduced or that certain automatic switchings between different sets of parameters are interlocked.

The latter may be explained by means of an example: European Patent Application 99 122 975.8 describes a fire detector that has an optical sensor for scattered light, a temperature sensor and a fire gas sensor. The electronic evaluation system of the detector comprises a fuzzy controller in which the signals of the individual sensors are combined and the particular type of fire is diagnosed. A special application-specific algorithm is provided for each type of fire and can be selected on the basis of the diagnosis. In addition, the detector comprises various sets of parameters for personnel protection and property protection between which on-line switching takes place under normal circumstances. If interference signals are now diagnosed in the case of the temperature sensor and/or in the case of the fire gas sensor, the switching between these sets of parameters is interlocked.

If fuzzy logic is used, one of the problems to be solved is to translate the knowledge stored in a database into linguistically interpretable fuzzy rules. Neuro-fuzzy methods developed for this purpose have not been convincing because they partly yield only fuzzy rules that are very difficult to interpret. On the other hand, so-called multiple resolution procedures offer a possibility of obtaining interpretable fuzzy rules. Their idea is to use a dictionary of membership functions that form a multiple resolution and to determine which are suitable membership functions for describing a control surface.

Figure 1 shows a diagram of such a multiple resolution. Row a shows the characteristic of a signal whose amplitude varies in the ranges small, medium and large. Correspondingly, row b shows the membership functions c1 "fairly small", c2 "medium" and c3 "rather large". These membership functions form a multiple resolution, which means that each membership function can be resolved into a sum of membership functions of a higher resolution level. This results in the membership functions c5 "very small", c6 "small to very small", c7 "very medium", c8 "large to very large" and c9 "very large" entered in row c. In accordance with row d, the triangular spline function c2 can therefore be converted, for example into the sum of the translated triangle functions of the higher level of row c.

In the Tagaki-Sugeno model, the fuzzy rules are expressed by the equation

$$R_i\text{: if } x \text{ is } A_i\text{, then } y_i = f_i\,(x_i) \qquad (1)$$

Here A_i's are linguistic expressions, x is the linguistic input variable and y is the output variable. The value of the linguistic input variables can be sharp or fuzzy. If, for example, x_i is a linguistic variable for temperature, the value $\hat{x}$ may be a sharp number such as "30(°C)" or a fuzzy quantity such as "approximately 25(°C)", "approximately 25" being itself a fuzzy set.

For a sharp input value, the output value of the fuzzy system is given by:

$$\hat{y} = \sum \beta_i \cdot f(\hat{x}) / \sum \beta_i \qquad (2)$$

where the degree of fulfilment $ß_i$ is given by the expression $ß_i = \mu_{Ai}\,(\hat{x})$ in which $\mu_{Ai}(\hat{x})$ denotes the membership function of the linguistic term A_i. In many applications, a linear function is taken: $f\,(\hat{x}) = a^T i \cdot \hat{x} + b_i$. If a constant b_i is taken to describe the sharp output value y, the system becomes:

$$R_i\text{: if } x \text{ is } A_i \text{ then } y_i = b_i \qquad (3)$$

If spline functions N^k are taken, for example as membership function $\mu_{Ai}(\hat{x}) = N^k[2^m(\hat{x}-n)]$, then the system of equation (3) is equivalent to

$$y_i = \Sigma b_i \cdot N^k\,[2^m(\hat{x}-n)] \qquad (4)$$

In this special case, the output y is a linear sum of translated and expanded spline functions. And that means that, given equation (4), the Tagaki-Sugeno model is equivalent to a multiple resolution spline model. And it follows from this that wavelet procedures can be applied.

Figure 2 shows a block diagram of a danger detector equipped with a neuro-fuzzy learning algorithm. The detector denoted by the reference symbol M is, for example, a fire detector and has three sensors 2 to 4 for fire parameters. For example, an optical sensor 2 is provided for scattered light measurement or transmitted light measurement, a temperature sensor 3 and a fire gas sensor, for example a CO sensor, 4, are provided. The output signals of the sensors 2 to 4 are fed to a processing stage 1 that has suitable means for processing the signals, such as, for example, amplifiers, and are passed from the latter to a microprocessor or microcontroller denoted below as μP 6.

In the μP 6, the sensor signals are compared both with one another and also individually with certain sets of parameters for the individual fire parameters. Of course, the number of sensors is not limited to three. Thus, only a single sensor may also be provided, and in this case, various characteristics, for example the signal gradient or the signal fluctuation, are extracted from the signal of the one sensor and investigated. Incorporated in the μP 6 are a neuro-fuzzy network 7 software and a validity test (validation) 8. If the signal resulting from the neuro-fuzzy network 7 is regarded as an alarm signal, an appropriate alarm signal is fed to an alarm-emitting device 9 or to an alarm centre. If the validation 8 reveals that interference signals occur repeatedly or regularly, the sets of parameters stored in the μP 6 are correspondingly corrected.

The neuro-fuzzy network 7 is a series of neuronal networks which use the symmetrical scaling functions $\varphi_{m,n}(x) = \varphi_{m,n,}(x) = \varphi[(x-n)\cdot 2^m]$ as an activation function. The scaling functions are such that $\{\varphi_{m,n}(x)\}$ form a multiple resolution. Each neuronal network uses activation functions of a given resolution. The m^{th} neuronal network optimizes the coefficients $\hat{c}_{m,n}$ with $f_m(x)$, the output of the m^{th} neuronal network.

$$f_m(x) = \Sigma\,\hat{c}_{m,n} \cdot \varphi_{m,n}(x) \ \ (\Sigma \text{ over all n's}) \qquad (5)$$

The coefficients $\hat{c}_{m,n}$ are calculated using the following equations:

$$\hat{c}_{m,n}(k) = \Sigma\,\tilde{\varphi}_{m,n}(x_i) \cdot y_i \,/\, \Sigma\,\tilde{\varphi}_{m,n}(x_i) \ \ (\Sigma \text{ over all i's = 1 to k}) \qquad (6)$$

where $y_k(x)$ is the k^{th} input point and $\tilde{\varphi}_{m,n}(x)$ is the dual function of $\varphi_{m,n}(x)$. The two equations (5) and (6) form the main algorithm of the neuro-fuzzy network.

In each iteration step, the values of the various neuronal networks are checked crosswise (validated), for which purpose a characteristic of the wavelet resolution is used, namely the one that the approximation coefficient $\hat{c}_{m,n}$ of a level m can be obtained from the approximation coefficients and wavelet coefficients of the level m-1 using the reconstruction algorithm or resolving algorithm.

In a preferred version, $\tilde{\varphi}_{m,n}(x)$ is a second-order spline function and $\varphi_{m,n}(x)$ is an interpolation function. In a second version, $\varphi_{m,n}(x)$ is a spline function and $\tilde{\varphi}_{m,n}(x)$ is the dual function of $\varphi_{m,n}(x)$. In a third version, $\tilde{\varphi}_{m,n}(x) = \varphi_{m,n}(x)$, where $\varphi_{m,n}(x)$ is the hair function. In these cases, it is possible to implement the learning algorithm in a simple microprocessor.

Figures 3a and 3b show two variants of a neuro-fuzzy network 7 and the associated validation stage 8. In the example of Figure 3a, the input signal is approximated in various resolution stages as the weighted sum of wavelets $\Psi_{m,n}$ and scaling functions $\varphi_{m,n}$ having a given resolution. The validation stage 8 compares the approximation coefficients $\hat{c}_{m,n}$ with the approximation coefficients and detailed coefficients of the wavelets at the level of the next lower resolution stage. Wavelet reconstruction filter coefficients are denoted by p and q.

In the example of Figure 3b, the input signal is approximated in various resolution stages as a weighted sum of scaling functions $\varphi_{m,n}$ having a given resolution. The validation stage 8 compares the approximation coefficients $\hat{c}_{m,n}$ with the approximation coefficients at the next-deeper resolution stage. Wavelet low-pass resolving coefficients are denoted by g.

The said coefficients can be determined in an estimator of the type shown in Figure 4 instead of in a neuro-fuzzy network 7. Said estimator is a so-called multiple resolution spline estimator that uses dual spline estimators based on the functions $\tilde{\varphi}_{m,n}(x)$ to estimate the coefficients $\hat{c}_{m,n}$ in the equation $f_m(x) = \hat{c}_{m,n} \cdot \varphi_{m,n}(x)$. Wavelet spline estimators are used for adaptively determining the appropriate resolution for locally describing a basic hypersurface in an on-line learning process. A known estimator is the Nadaraya-Watson estimator with which the equation of the hypersurface f(x) is estimated using the following expression:

$$f(x) = \sum_{k=1}^{k_{max}} K((x-x_k)/\lambda) \cdot y_k \Big/ \sum_{k=1}^{k_{max}} K((x-x_k)/\lambda). \qquad (6)$$

Nadaraya-Watson estimators have two interesting characteristics - they are estimators of the local mean quadratic deviation and it can be shown that they are so-called Bayes estimators of (x_k,y_k) in the case of a random design, where (x_k,y_k) are iid copies of a continuous random variable (X, Y).

The spline functions $\varphi(x)$ and their dual function $\tilde{\varphi}(x)$ can be used as estimators. We first use the function $\tilde{\varphi}(x)$ to estimate f(x) using $\lambda = 2^{-m}$ (m is an integer) from x_n, where $x_n \cdot 2^m \varepsilon Z$:

Using the symmetry of $\tilde{\varphi}(x)$, equation (6) for the dual spline function is equivalent to the use of an estimator centred at x_n:

$$\hat{f}(x_n) = \sum_{k=1}^{k_{max}} \tilde{\varphi}((x_k-x_n) \cdot 2^m) \cdot y_k / \sum_{k=1}^{k_{max}} \tilde{\varphi}((x_k-x_n) \cdot 2^m). \qquad (7)$$

The expected value of the numerator in equation (7) is proportional to the approximation coefficients $c_{m,n}$. Equation (6) yields an estimate of $\hat{c}_{m,n}$ in $f_m(x) = \Sigma\, \hat{c}_{m,n} \cdot \varphi_{m,n}(x)$:

$$\hat{c}_{m,n} = \hat{f}(x_n). \qquad (8)$$

In Figure 4, the available data (values) are denoted by a small square, their projection on dual spline functions by a small circle and the estimate on a regular grid by a small cross.

To validate the coefficient $\hat{c}_{,n}$, two conditions are necessary:

$$|\, \hat{c}_{m,n} - \sum_{p} g_{p-2n} \cdot \hat{c}_{m+1,p} \,| < \Delta \qquad (9)$$

where the filter coefficients g correspond to the low-pass resolving coefficients for spline functions. In addition it is required that

$$|\, \sum_{k=1}^{k_{max}} \tilde{\varphi}((x_k-x_n) \cdot 2^m) \,| > T \qquad (10)$$

so that divisions by very small values are prevented.

The strength of this method is that the calculation of a coefficient $\hat{c}_{m,n}$ requires the storage of only two values, the numerator and the denominator in equation (7). The method is therefore well suited for on-line learning using a simple microprocessor having low storage capacity.

The method can easily be adapted to density estimation by replacing equations (7) and (8) by the following equation:

$$\hat{c}_{m,n} = 1/k_{max} \cdot \sum_{k=1}^{k_{max}} \widetilde{\varphi}_{m,n}(x_k) \cdot y_k \qquad (11)$$

Patent Claims

1. Method for processing the signals of an detector unit that has at least one sensor (2, 3, 4) for monitoring danger parameters and an electronic evaluation system (1) that is assigned to the at least one sensor (2, 3, 4) and in which the signals of the at least one sensor (2, 3, 4) are compared with specified parameters, characterized in that the signals of the at least one sensor (2, 3, 4) are analysed on the basis of whether they occur increasingly frequently or regularly and in that signals occurring increasingly frequently or regularly are classified as interference signals.

2. Method according to Claim 1, characterized in that the classification of signals as interference signals triggers an appropriate adjustment of the parameters.

3. Method according to Claim 2, characterized in that, if interference signals occur, the validity of the result of the analysis of the signals of the at least one sensor (2, 3, 4) is checked prior to the adjustment of the parameters and in that the parameters are adjusted as a function of the result of this validity test.

4. Method according to Claim 3, characterized in that the validity is tested by methods based on multiple resolution.

5. Method according to Claim 4, characterized in that wavelets, preferably "biorthogonal" or "second generation" wavelets or "lifting schemes" are used for the validity test.

6. Method according to Claim 5, characterized in that the expected values for the approximation coefficients or the approximation coefficients and detailed coefficients of the wavelets are determined and compared at different resolutions.

7. Method according to Claim 6, characterized in that the said coefficients are determined in an estimator or by means of a neuronal network.

8. Danger detector having means for carrying out the method according to Claim 1, having at least one sensor (2, 3, 4) for a danger parameter and having an electronic evaluation system (1), comprising a microprocessor (6), for evaluating and analysing the signals of the at least one sensor (2, 3, 4), characterized in that the microprocessor (6) comprises a software program having a learning algorithm, based on multiple resolution, for analysing the signals of the at least one sensor (2, 3, 4).

9. Danger detector according to Claim 9, characterized in that, on the one hand, the said sensor signals are analysed by the learning algorithm for their repeated or regular

occurrence and, on the other hand, a validity test is carried out on the result, and in that the learning algorithm for the validity test uses wavelets, preferably "biorthogonal" or "second generation" wavelets.

10. Danger detector according to Claim 9, characterized in that the learning algorithm uses neuro-fuzzy methods.

11. Danger detector according to Claim 10, characterized in that the learning algorithm comprises the two equations

$f_m(x) = \sum \hat{c}_{m,n} \cdot \varphi_{m,n}(x)$ (Σ over all n's) and

$\hat{c}_{m,n}(k) = \sum \tilde{\varphi}_{m,n}(x_i) \cdot y_i / \sum \tilde{\varphi}_{m,n}(x_i)$ (Σ over all i's = 1 to k)

in which $\varphi_{m,n}$ denotes scaling functions, $\hat{c}_{m,n}$ denotes approximation coefficients and y_k denotes the k^{th} input point of the neuronal network and $\tilde{\varphi}_{m,n}$ is the dual function of $\varphi_{m,n}$.

Abstract

The signals of a danger detector that has at least one sensor (2, 3, 4) for monitoring danger parameters and an electronic evaluation system (1) assigned to the at least one sensor (2, 3, 4) are compared with specified parameters. In addition, the signals are analysed with regard to whether they occur increasingly frequently or regularly, and signals that occur increasingly frequently or regularly are classified as interference signals. The classification of signals as interference signals triggers an appropriate adjustment of the parameters. If interference signals occur, the validity of the result of the analysis of the signals of the at least one sensor (2, 3, 4) is checked prior to the adjustment of the parameters, and the parameters are adjusted as a function of the result of said validity test.

A danger detector having means for carrying out said method contains at least one sensor (2, 3, 4) for a danger parameter and an electronic evaluation system (1), comprising a microprocessor (6), for evaluating and analysing the signals of the at least one sensor (2, 3, 4). The microprocessor (6) comprises a software program having a learning algorithm, based on multiple resolution, for analysing the signals of the at least one sensor (2, 3, 4).

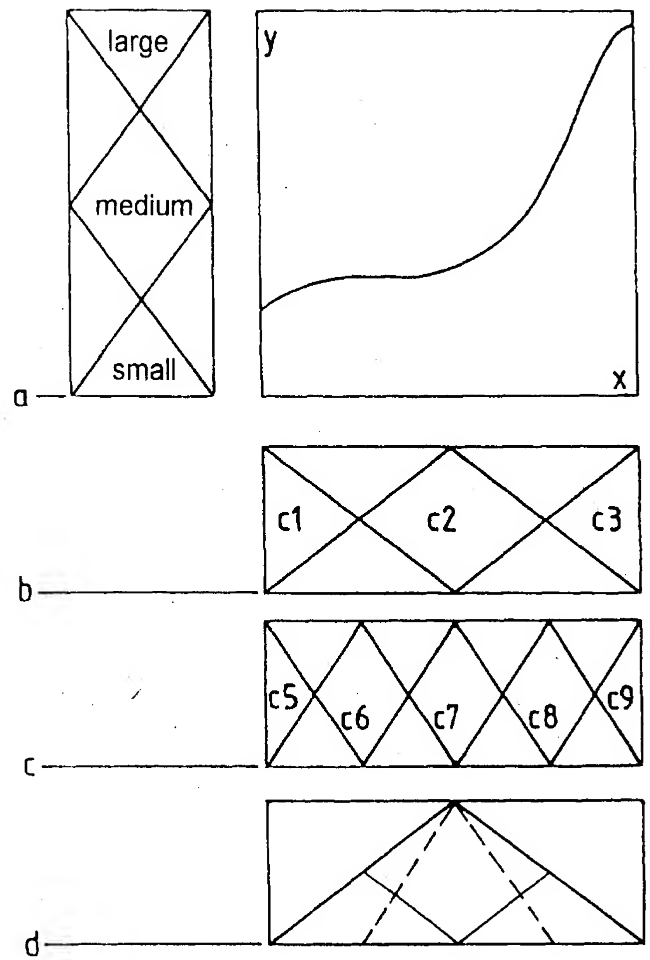
large
medium
small
y
x
a
b
c1
c2
c3
c
c5
c6
c7
c8
c9
d

FIG.1

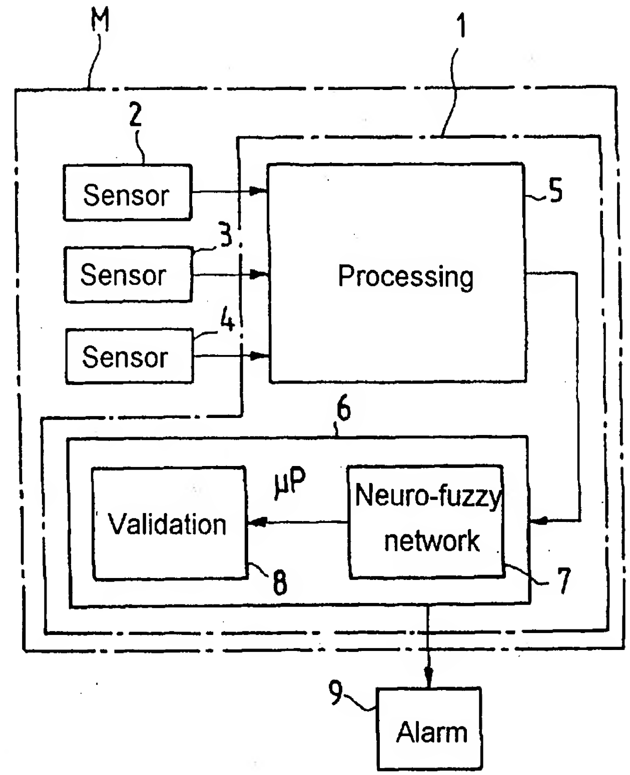
M
1
2
Sensor
3
Sensor
4
Sensor
Processing
5
6
Validation
μP
Neuro-fuzzy network
8
7
9
Alarm

FIG. 2

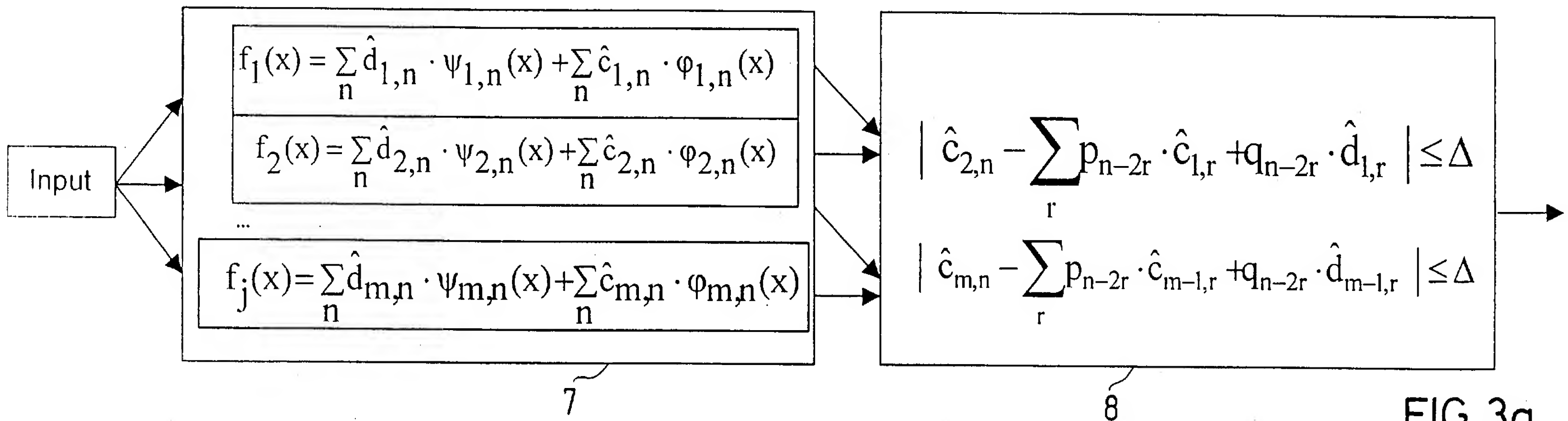
Input
$f_1(x)=\sum_n \hat{d}_{1,n}\cdot\psi_{1,n}(x)+\sum_n \hat{c}_{1,n}\cdot\varphi_{1,n}(x)$
$f_2(x)=\sum_n \hat{d}_{2,n}\cdot\psi_{2,n}(x)+\sum_n \hat{c}_{2,n}\cdot\varphi_{2,n}(x)$
...
$f_j(x)=\sum_n \hat{d}_{m,n}\cdot\psi_{m,n}(x)+\sum_n \hat{c}_{m,n}\cdot\varphi_{m,n}(x)$
$|\hat{c}_{2,n}-\sum_r p_{n-2r}\cdot\hat{c}_{1,r}+q_{n-2r}\cdot\hat{d}_{1,r}|\le\Delta$
$|\hat{c}_{m,n}-\sum_r p_{n-2r}\cdot\hat{c}_{m-1,r}+q_{n-2r}\cdot\hat{d}_{m-1,r}|\le\Delta$
7
8

FIG. 3a

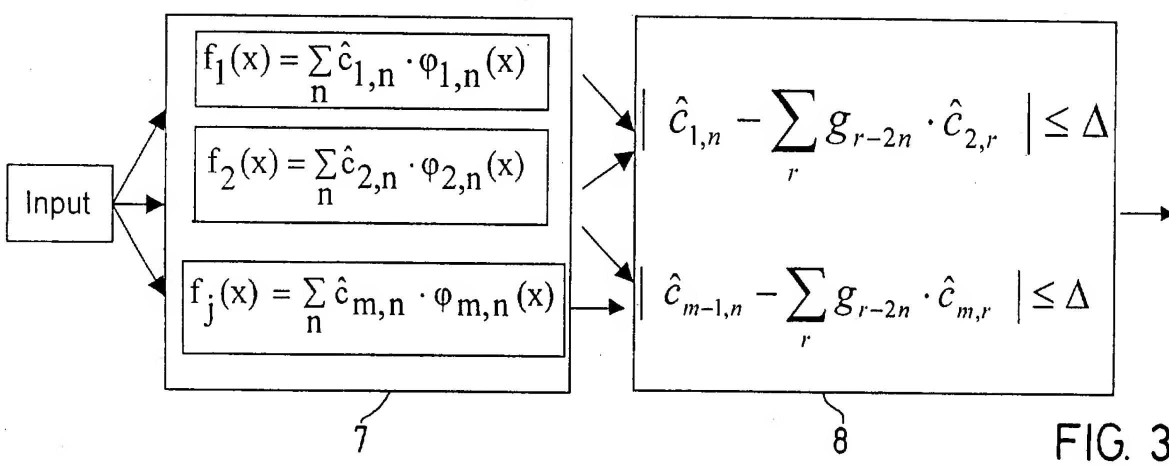
Input
$f_1(x)=\sum_n \hat{c}_{1,n}\cdot\varphi_{1,n}(x)$
$f_2(x)=\sum_n \hat{c}_{2,n}\cdot\varphi_{2,n}(x)$
$f_j(x)=\sum_n \hat{c}_{m,n}\cdot\varphi_{m,n}(x)$
$|\hat{c}_{1,n}-\sum_r g_{r-2n}\cdot\hat{c}_{2,r}|\le\Delta$
$|\hat{c}_{m-1,n}-\sum_r g_{r-2n}\cdot\hat{c}_{m,r}|\le\Delta$
7
8

FIG. 3b

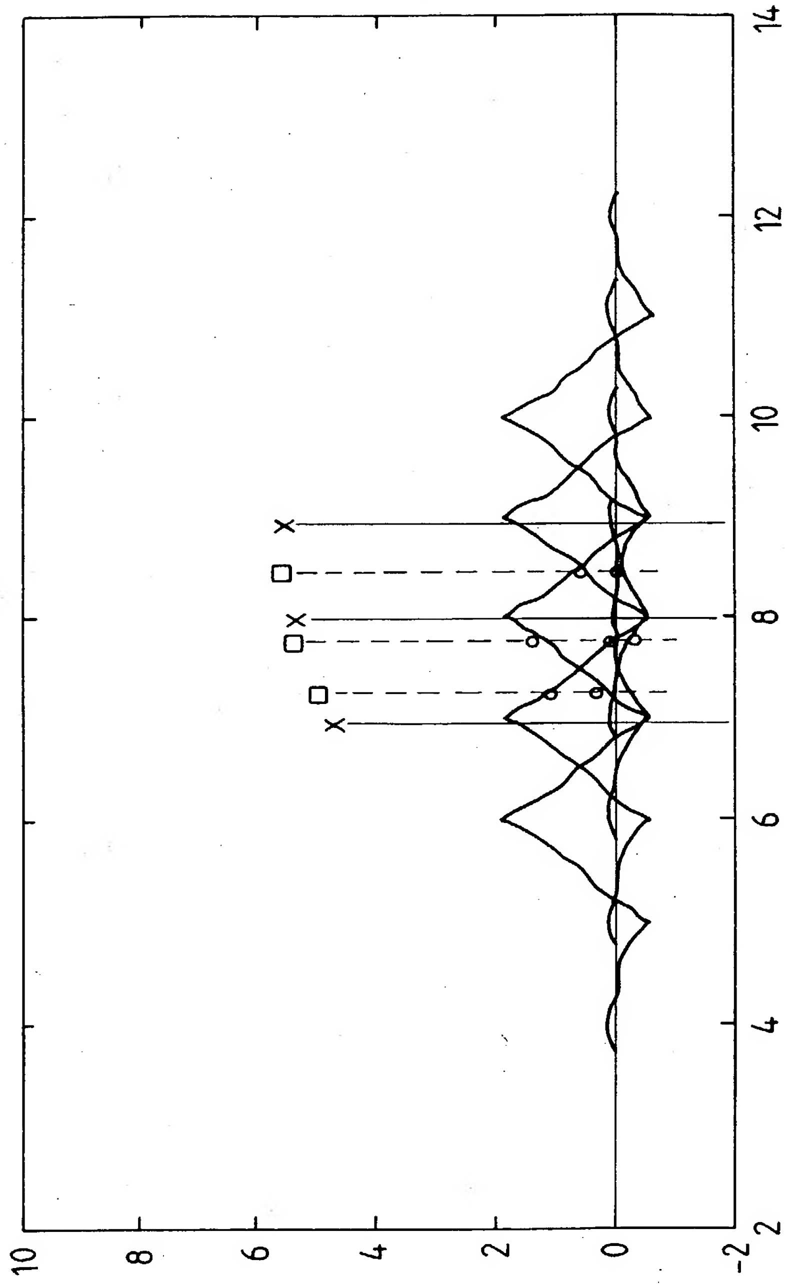

FIG. 4

#5

COMBINED DECLARATION AND POWER OF ATTORNEY

(Original, Design, National Stage of PCT, Divisional, Continuation or C-I-P Application)

As a below named inventor, I hereby declare that:
My residence, post office address and citizenship are as stated below next to my name; I believe I am the original, first and sole inventor (*if only one name is listed below*) or an original, first and joint inventor (*if plural names are listed below*) of the subject matter which is claimed and for which a patent is sought on the invention entitled:

METHOD FOR PROCESSING THE SIGNALS OF A DANGER DETECTOR AND DANGER DETECTOR HAVING MEANS FOR PERFORMING THE METHOD

This declaration is of the following type:

[] original
[] design
[X] national stage of PCT/CH01/00136 filed March 15, 2000
[] divisional
[] continuation
[] continuation-in-part (C-I-P)

the specification of which: *(complete (a), (b), or (c))*

(a) [] is attached hereto.
(b) [X] was filed on October 25, 2001 as Application Serial No. 10/019,362.
(c) [] was described and claimed in PCT International Application No. ________ filed____________ and was amended on *(if applicable).*

Acknowledgment of Review of Papers and Duty of Candor

I hereby state that I have reviewed and understand the contents of the above identified specification, including the claims, as amended by any amendment referred to above.

I acknowledge the duty to disclose information which is material to the patentability of the subject matter claimed in this application in accordance with Title 37, Code of Federal Regulations § 1.56.

[ ] In compliance with this duty there is attached an information disclosure statement. 37 CFR 1.98.

Priority Claim

I hereby claim foreign priority benefits under Title 35, United States Code, § 119(a)-(d) of any foreign application(s) for patent or inventor's certificate or of any PCT International Application(s) designating at least one country other than the United States of America listed below and have also identified below any foreign application(s) for patent or inventor's certificate or any PCT International Application(s) designating at least one country other than the United States of America filed by me on the same subject matter having a filing date before that of the application on which priority is claimed

(complete (d) or (e))

(d) [] no such applications have been filed.
(e) [X] such applications have been filed as follows:

PRIOR FOREIGN/PCT APPLICATION(S) FILED WITHIN 12 MONTHS (6 MONTHS FOR DESIGN) PRIOR TO SAID APPLICATION			
COUNTRY APPLICATION NO.	DATE OF FILING (day, month, year)	DATE OF ISSUE (day, month, year)	PRIORITY CLAIMED UNDER 35 USC 119
EP 00 10 5438	14 August 2000		[X] YES NO []
			[] YES NO []
			[] YES NO []
ALL FOREIGN APPLICATION[S], IF ANY, FILED MORE THAN 12 MONTHS (6 MONTHS FOR DESIGN) PRIOR TO SAID APPLICATION			
			[] YES NO []
			[] YES NO []
			[] YES NO []

Claim for Benefit of Prior U.S. Provisional Application(s)

I hereby claim the benefit under Title 35, United States Code, § 119(e) of any United States provisional application(s) listed below:

Provisional Application Number	Filing Date

Claim for Benefit of Earlier U.S./PCT Application(s) under 35 U.S.C. 120

(complete this part only if this is a divisional, continuation or C-I-P application)

I hereby claim the benefit under Title 35, United States Code, § 120 of any United States application(s) or PCT international application(s) designating the United States of America that is/are listed below and, insofar as the subject matter of each of the claims of this application is not disclosed in the prior application(s) in the manner provided by the first paragraph of Title 35, United States Code § 112, I acknowledge the duty to disclose information as defined in Title 37, Code of Federal Regulations, § 1.56 which occurred between the filing date of the prior application(s) and the national or PCT international filing date of this application:

(Application Serial No.)	(Filing Date)	(Status) (patented, pending, abandoned)
PCT/CH01/00136	March 15, 2000	Pending

Power of Attorney

As a named inventor, I hereby appoint Robert Neuner, Reg. No. 24,316; Richard G. Berkley, Reg. No. 25,465; Bradley B. Geist, Reg. No. 27,551; James J. Maune, Reg. No. 26,946; John D. Murnane, Reg. No. 29,836; Henry Tang, Reg. No. 29,705; Robert C. Scheinfeld, Reg. No. 31,300; John A. Fogarty, Jr., Reg. No. 22,348; Louis S. Sorell, Reg. No. 32,439; Rochelle K. Seide Reg. No. 32,300; Gary M. Butter, Reg. No. 33,841; Lisa B. Kole, Reg. No. 35,225; and Anthony Giaccio, Reg. No. 39,684 of the firm of BAKER BOTTS L.L.P., with offices at 30 Rockefeller Plaza, New York, New York 10112, as attorneys to prosecute this application and to transact all business in the Patent and Trademark Office connected therewith

SEND CORRESPONDENCE TO:	DIRECT TELEPHONE CALLS TO:
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I hereby declare that all statements made herein of my own knowledge are true and that all statements made on information and belief are believed to be true; and further that these statements were made with the knowledge that willful false statements and the like so made are punishable by fine or imprisonment, or both, under Section 1001 of Title 18 of the United States Code and that such willful false statements may jeopardize the validity of the application or any patent issued thereon.

1-00

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DATE 03/01/2008	SIGNATURE OF INVENTOR M. Thuillard			
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RESIDENCE & CITIZENSHIP	CITY	STATE or FOREIGN COUNTRY	COUNTRY OF CITIZENSHIP	
POST OFFICE ADDRESS	POST OFFICE ADDRESS	CITY	STATE or COUNTRY	ZIP CODE
DATE	SIGNATURE OF INVENTOR			
FULL NAME OF THIRD JOINT INVENTOR, IF ANY	LAST NAME	FIRST NAME	MIDDLE NAME	
RESIDENCE & CITIZENSHIP	CITY	STATE or FOREIGN COUNTRY	COUNTRY OF CITIZENSHIP	
POST OFFICE ADDRESS	POST OFFICE ADDRESS	CITY	STATE or COUNTRY	ZIP CODE
DATE	SIGNATURE OF INVENTOR			
FULL NAME OF FOURTH JOINT INVENTOR, IF ANY	LAST NAME	FIRST NAME	MIDDLE NAME	
RESIDENCE & CITIZENSHIP	CITY	STATE or FOREIGN COUNTRY	COUNTRY OF CITIZENSHIP	
POST OFFICE ADDRESS	POST OFFICE ADDRESS	CITY	STATE or COUNTRY	ZIP CODE
DATE	SIGNATURE OF INVENTOR			

Check proper box(es) for any added page(s) forming a part of this declaration

[ ] Signature for fifth and subsequent joint inventors. Number of pages added __________.

[ ] Signature by administrator(trix), executor(trix) or legal representative for deceased or incapacitated inventor. Number of pages added ____________________________________.

[ ] Signature for inventor who refuses to sign, or cannot be reached, by person authorized under 37 CFR 1.47. Number of pages added __________________.